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Modelling Stochastic Optimization to Energy and Reserve Market in a Microgrid Environment

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Resumo

Aqui é apresentado o resumo escrito em Português.

Nos últimos anos tem se assistido a um aumento da procura por eletricidade e essa tendencia deve manter-se no futuro. Novas economias têm-se desenvolvido um pouco por todo o mundo e a forma tradicional de organização do sistema eletrico de energia não consegue dar resposta aos desafios do mundo atual. A recente reestruturação dos mercados de eletricidade possibilitou uma maior competetividade do sector eletrico, trazendo benefícios aos produtores e consumidores.

A aposta num esquema descentralizado, com grande incidência de produção dispersa por parte de recursos renováveis, trás inumeros benefícios, quer para os produtores e consumidores, quer para o ambiente. No entanto este tipo de geração, nomeadamente a geração renovável requer um maior e mais eficaz controlo, uma vez que há uma grande incerteza na disponibilidade destes recursos, estando dependente das condições atmosféricas vigentes. A incerteza resultante deste tipo de recursos tem custos para o sistema, pois o operador da rede não tem informação util sobre a sua disponibilidade e o despacho dos geradores pode não ser eficaz. Para fazer face ao aumento da incerteza proveniente da proliferação deste tipo de recursos, a comunicação entre os vários participantes do sistema assume uma maior importância.

Novos modelos organizacionais do sistema tem surgido tais como microredes e *virtual power plants*, modelos estes que apresentam, em relação ao modelo tradicional, várias vantagens descritas ao longo da dissertação. Esta dissertação aborda a gestão de energia e reserva numa microrede. O objectivo é determinar o despacho ótimo de energia e reserva que minimiza os custos totais para o operador da microrede.

Uma importante contribuição desta dissertação é a concepção, *design* e desenvolvimento de uma metodologia estocástica para o escalonamento de energia e reserva, na presença de incerteza, no âmbito de uma microrede. Neste contexto foi desenvolvido um programa estocástico de dois níveis, modulado por programação linear. A incerteza no sistema é representada por cenários com a respectiva probabilidade associada.

Esta dissertação contribui também com a incorporação de um modelo DC da rede com o objetivo de modular as restrições da microrede e evitar congestionamentos. O modelo DC implica uma série de simplificações que linearizam e simplificam o problema, tornando mais fácil a sua implementação. O resultado é um problema com menos dados que requer menos tempo e capacidade de processamento.

Outra contribuição fundamental desta dissertação é a inclusão de um modelo AC linearizado, permitindo uma mais correta aproximação ao comportamento de uma microrede real. Ao contrário do modelo DC, o modelo AC é capaz de modular potencia ativa e reativa bem como o módulo e fase das tensões nos barramentos. Com a incorporação do modelo AC, o operador da migrorede está preparado para lidar com eventuais congestionamentos e sobretensões que possam surgir numa rede com grande penetração de recursos renováveis, onde o transito de potencias bidirecional é bastante frequente.

Os modelos descritos são aplicados a uma microrede constituida por uma rede de distribuição de 11 kV, considerando um cenário de penetração renovavel para o ano de 2050. Estão conectados à microrede 1 agregador external supplier (representando a ligação a rede de 33kV), 3 agregadores de cogeração, 2 agregadores eólicos e 22 agregadores fotovoltaicos. Este teste permite validar os modelos propostos, mostrando a sua aplicabilidade a futuros sistemas eletricos de energia com grandes níveis de incerteza.

Abstract

In recent years there has been an increase in demand for electricity and this trend is expected to continue in the future. New economies have been developing around the world, and the traditional way of organizing the power system fails to respond to the challenges of today's world. The recent restructuring of electricity markets and the shift to a decentralized scheme of the power system have made it possible to have a higher level of competition within the electricity sector, bringing benefits to consumers and producers.

A decentralized scheme, with a high incidence of distributed generation from renewable energy sources, brings numerous benefits to producers, consumers and the environment. However, this type of generation, namely the renewable energy generation, requires a greater and more effective control, since they have an uncertain and variable production behavior, depending on the current atmospheric conditions. The uncertainty related to these resources implies costs to the system, since they are not fully dispatchable, and therefore network operators need to find ways to ensure system balance and reliability, like procuring more reserve. To cope with the increase in uncertainty arising from the proliferation of this type of resources, communication between the various participants of the system assumes greater importance.

New organizational models of the system have emerged, such as Microgrids (MG) and Virtual Power Plants (VPP). These models present several advantages over the traditional power system, as described throughout this dissertation. This dissertation deals with the energy and reserve management in a microgrid. The objective is to determine the optimal energy and reserve dispatch that minimizes the total operating costs of the MG operator.

One important contribution of this work is the conception, design and development of a stochastic energy and reserve scheduling to deal with uncertain generation in the scope of a MG. In this context, a two-stage stochastic technique modulated as linear programming was developed. The uncertainty in the system is represented by scenarios with an associated probability.

In addition, this dissertation also contributes with the incorporation of the DC Optimal Power Flow (OPF) to the stochastic scheduling problem. This allows to model the network constraints of the MG and avoid network congestion. The DC OPF implies a series of simplifications which linearize the problem and make it easier to implement. This results in a problem with less data, requiring less time and processing power to compute than the full AC OPF, which is a nonlinear and non-convex problem.

Another major contribution is the inclusion of a linearized AC OPF. This OPF models also reactive power and voltage magnitude, allowing a more accurate approximation of the natural MG behavior. The method is able to model both active and reactive power and voltage magnitude as opposed to DC OPF. This approach enables the MG operator to be ready to face potential congestion and voltage problems that may arise in the MG full of DER where bi-directional power flow is common.

The models were applied to a MG composed by an 11kV distribution network, for a 2050 scenario, with high penetration of renewable energy sources. To the MG are connected 1 external

supplier (representing the upstream connection with the 33kV Medium Voltage (MV) line), 3 CHP aggregators, 2 wind aggregators and 22 PV aggregators. This test case allows the assessment and validation of the proposed models, showing their applicability and scalability to future power systems, full of distributed energy resources, with high levels of uncertainty.

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"The fewer moving parts, the better"

Christian Cantrell

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Abbreviations and nomenclature

Abbreviations

AC	Alternate Current
AS	Ancillary Services
CERTS	Consortium for Electric Reliability Technology Solutions
DC	Direct Current
DG	Distributed Generation
DNO	Distribution Network Operator
CHP	Combined Heat and Power
DER	Distributed Energy Resource
DSO	Distribution System Operator
ESS	Energy Storage System
EMS	Energy Management System
EV	Electric Vehicle
EVPI	Expected Value of the Perfect Information
FERC	Federal Energy Regulatory Commission
ISO	Independent System Operator
LDR	Linear Decision Rules
MG	Microgrid
MV	Medium Voltage
NERC	North American Electric Reliability Corporation
OPF	Optimal Power Flow
RES	Renewable energy sources
VPP	Virtual Power Plant
VSS	Value of the Stochastic Solution
WECC	Western Electricity Coordinating Council

Nomenclature

Sets

dg	Index of distributed generation units
l	Index of consumers
pv	Index of photovoltaic units
su	Index of external suppliers
w	Index of wind power producers
ω	Index of scenarios

Parameters

C	Cost (m.u.)
$\pi\omega$	Probability of scenario ω
ΔP	Deviation of power production for renewable energy sources
$\hat{P}$	Conditional mean forecast of renewable generators in the day-ahead stage
B	Imaginary part in admittance matrix
G	Real part in admittance matrix
Px	Active power part of piecewise approximation of apparent power
Py	Reactive power part of piecewise approximation of apparent power
ang_k	Slops of the piecewise function for apparent power approximation
α	Slops of the piecewise function for cosine approximation
N	Number of units per resource type
T	Time horizon

Variables

P	Active power production
R	Reserve scheduled
r	Activation of reserve in the second-stage problem
Q	Reactive power production
S	Apparent power production
$Pflow$	Active injected power in nodes and branches i, j
θ	Voltage angle
V	Voltage magnitude
PWL	Piecewise linearization of cosine function

Subscripts

DG	Distributed generation units
DR	Demand response units
L	Loads
PV	Photovoltaic units
SU	External suppliers
W	Wind power producers

Superscripts

E	Energy
up	Upward reserve
dw	Downward reserve
DA	Day-ahead stage
RT	Real-time stage
act	Activation of reserve
cut	Generation curtailment power of DG units
spill	Spillage of renewable power
shed	Load shedding
Max	Maximum threshold of a variable
Min	Minimum threshold of a variable

Chapter 1

Introduction

1.1 Background and motivation

Carbon emissions have caused an increase of 4 ^{o}C of the global temperature, this increase could cause a sufficient eventual sea level rise to submerge land that is currently home to 470–760 million people globally [1]. Over the past years there has been an accelerated growth in the global economy. As a consequence, the emissions resulting from the electricity demand have skyrocketed and the trend is to maintain this level of growth as new economies are arising. An overview of the past years situation considering the emissions topic can be found in [2]. The environmental concerns have never been so important and these factors are preponderant to a change the power production paradigm.

Despite the efforts made to develop more power systems fed by Renewable Energy Sources (RES), reducing the emissions of greenhouse gases, the fact is that the actual panorama still implies the use of large amount of fossil fuels to fulfill the energy needs of the populations specially in developing countries.

What is still a reality today is a centralized scheme where the production is assured by large power plants (working mainly on fossil fuels) and transported through long distances to the consumers. This scheme has negative aspects such as:

- Efficiency: By generating the energy in large power plants and transporting it through large distances the associated losses are high;

- Reliability: There is a high level of dependency on the power plants and if an outage occurs on any of them, a large amount of consumers can face a blackout. In addition, a great amount of the equipment in use today was designed to meet the requirements of the past and is outdated today. These aspects make the system less reliable and the maintenance more complex and expensive;

- Environment: The centralized generation is mainly assured by non-RES and that contributes to a great set of concerns, like air pollution, water use and discharge, land use, and waste generation.

In this context, many countries are trying to move from this form of centralized power to a national network of MGs [3], aiming to reduce power losses and move towards a clean power system.

A MG is a network that comprises various Distributed Energy Resources (DER), such as wind turbines, photovoltaic (PV) cells, small-hydro plants, Combined Heat and Power (CHP), small diesel generators, etc. A DER can be defined as an electric power generator within the distribution network or on the customer side of the network, usually with a capacity of the sources varying from few kW to 1-2 MW [4], DER can also include Energy Storage Systems (ESS), such as batteries or super capacitors [5, 6]. MGs can operate interconnected with the main distribution grid, or in an autonomous way (island mode) in case of external faults. From the grid operator point of view, a MG can be seen as a controlled entity within the power system that can be operated as a single aggregated load or generator [7] and, given attractive remuneration, as a small source of power or ancillary services supporting the network [4]. A VPP is an Energy Management System (EMS) in charge of aggregating and managing the DER. The VPP enable the collective participation of DER in electricity markets. The VPP provides a centralized control for multiple DERs [8], allowing them to provide energy or even ancillary services. The VPP enable the collective participation of DER in electricity markets

Most MGs and VPPs take advantage of RES such as solar, wind, and hydro power to being able to participate in the market with low generation prices and low emissions. ESS, like batteries, play an important role, by storing the energy generated by intermittent RES to increase the power system reliability, and to ease the demand on the power grid. Distributed Generation (DG) solves many of the centralized system most troubling issues such as:

- Efficiency: Generation is closer to the consumers, so the line losses and the costs of material to the installation are minimized.
- Environmental: A system full of DER, particularly one that uses RES, has more positive environmental impact than the traditional power system, specifically when it comes to land use and air pollution;
- Reliability: The maintenance on the components and the potential increase on the installed capacity is much easier to perform. The fact of being a decentralized scheme implies a higher level of autonomy and reliability (a failure in one section does not disrupt the entire system);
- Costs: Nowadays the cost of the non-RES is much higher than RES and it tends to increase more and more in the future. Technological advances are bringing down the manufacturing and maintenance costs of the DER. Thus, the tendency is to replace non-RES generation by RES generation.

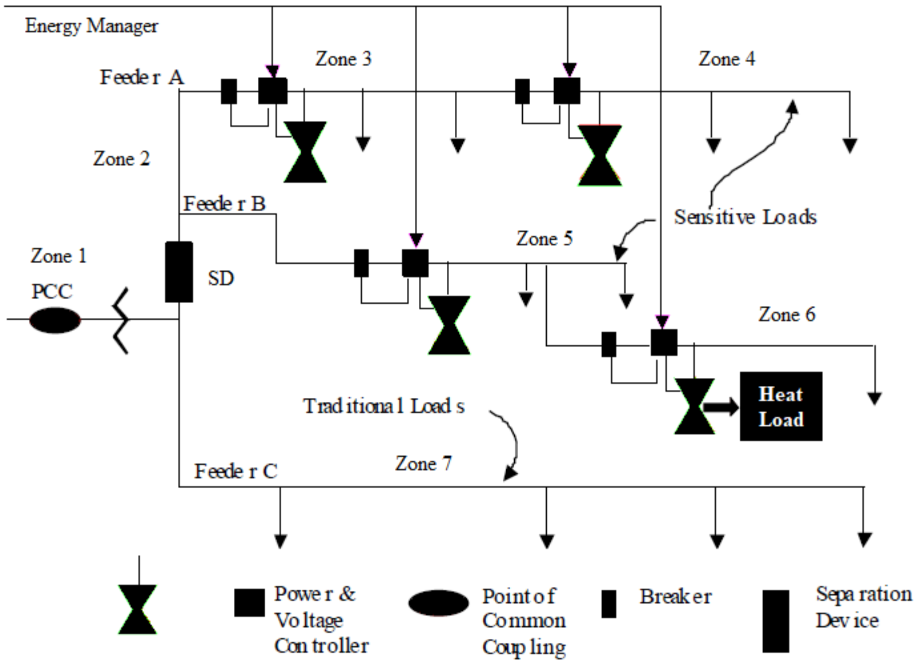

Figure 1.1: Vision of the MG by CERTS, adapted from [9]

The fast development of information and communications technologies is benefiting the appearance of more decentralized business models to efficiently manage DERs. This business models range from the MG and VPP concepts to the deployment of new distributed services like aggregations of energy resources or Electric Vehicle (EV) fleet [9].

The literature contemplates two main architectures of MGs so far, the European one described in MICROGRIDS and MORE MICROGRIDS projects [10] and the American one developed by the Consortium for Electric Reliability Technology Solutions (CERTS) [11]. The main difference between them is that CERTS provides also heat while the European MG is conceived to provide only power [9]. This differences are detailed in the figures 1.1 and 1.2.

Microgrid markets

MG energy markets provide small-scale producers and consumers with a market platform to trade locally generated energy within their community. MGs promote the consumption of energy close to its generation and, therefore, foster sustainability and the efficient use of local resources [12]. Nowadays, renewable power producers as an aggregation within a MG are, not only able, but also required to participate in the electricity markets under conditions similar to those for conventional power producers [13]. In fact, a MG can participate either in the energy market and in ancillary services markets. Since MGs aim to integrate more RES in the system and this type of resources imply uncertainty and have a higher complexity in terms of communication between its participants, it is indispensable to have a well function structure to operate the MG and to ease the

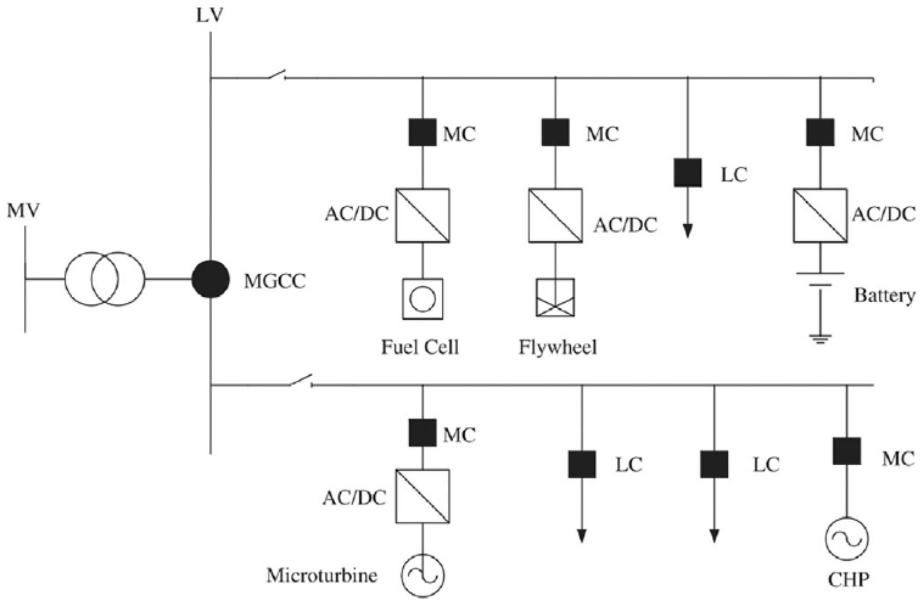

Figure 1.2: Vision of the MG by MICROGRID project, adapted from [9]

interconnection of it with the markets.

MGs buy or sell energy to or from the main grid through an aggregator. Aggregators take care of local distribution systems and greatly reduce the workload burdens on both Independent System Operator (ISO) and the local Distribution System Operator (DSO), particularly when there are great numbers of retail market participants in the networks [8].

1.2 Dissertation objectives and contributions

This dissertation focus on the RES as the main providers of electricity. This type of resources require a more efficient management because they are associated with uncertainty. Unlike coal or oil, RES cannot be efficiently stored yet, and their availability rely on many factors, mainly the present atmospheric conditions. A larger amount of RES on the system implies a higher level of uncertainty, and that requires a more efficient management of the energy, as well as the procurement of proper levels of reserve. These are one of the most important challenges the power systems is facing. Nowadays, there are ways for the system operator to deal with the uncertain RES generation, by scheduling sufficient reserve to be activated whenever needed. This scheduled reserve is meant to help the power system dealing with fluctuations of energy in both demand and production side when contingencies occur.

Nevertheless, inside the MG a small internal market is expected to operate in order to accommodate the DER generation of the MG. In [4] it is described how this optimization is done depending on the control approaches followed for the MG (more centralized or less centralized).

In this context, this dissertation offers a contribution to the energy and reserve scheduling within a MG, by introducing new approaches to solve the problem. The objective is to develop a program capable of providing optimal solutions for energy and reserve schedule in a MG, at the minimum cost for the MG operator. The main contributions under the scheduling problem of a MG are threefold:

- Conception, design and development of a stochastic energy and reserve scheduling to deal with uncertain production in the scope of a MG;
- Incorporation of the DC Optimal Power Flow (OPF) in the scheduling problem to avoid network congestion;
- Integration of a recent AC OPF linearization to comply with distribution network characteristics. This new AC OPF linearization approximates the natural behavior of the network by considering both active and reactive power. Thus, the model is ready to give feasible solutions to the decision-maker, by solving potential congestion and voltage problems that may arise in a MG full of DER where bi-directional power flow is common.

1.3 Dissertation structure

This dissertation is organized into five chapters. In addition to the introduction chapter, four more chapters are included, as described in the following paragraphs.

Chapter 2 covers the state of the art of this topic. The energy scheduling problem is explored, taking into account the formulation type and objective function, solving method, uncertainty, demand response, reactive power and emissions. It is covered the topic of energy and reserve in MGs and VPPs. Also in this chapter previous work in this topic is presented.

Chapter 3 covers the energy and reserve market model. The two-stage stochastic linear programming is described as a way of dealing with the uncertain generation within a MG. Two optimization models were designed. Firstly, the stochastic problem under the DC model of the network (simplest OPF model, also called in this dissertation as the benchmark model) was implemented. Secondly, the design of the stochastic problem with a full linearized AC OPF. This approach is convex and completely linear, as the non-convexities and nonlinearities of the standard AC OPF were linearized.

Chapter 4 presents the outline of the MG test and the results of the simulation for both DC and AC stochastic approaches. In addition, different network characteristics were assessed to evaluate the effects of different system parameters on the solution such as the number of scenarios and the reactance/resistance ratio of the distribution lines. Quality metrics (such as value of the stochastic solution and expected value of perfect information) for the assessment of the stochastic solution were also performed and discussed.

Chapter 5 highlights the most important conclusions of the work developed and described in this dissertation. Future developments and ideas for improving the proposed approaches are emphasized.

Chapter 2

State of art

2.1 Introduction

MGs and VPPs are two distribution network concepts that can participate in active network management of a smart grid [8]. In chapter 1 it was given a definition of these two concepts, in this chapter it will be discussed this two terms in a market overview and there will be presented the reasons why MGs and VPPs can be the future paradigm of the electrical system. [4] and [10] investigate the market configurations in MV and LV networks inside a MG, the control approaches followed and the security within the MICROGRIDS and MOREMICROGRIDS (Europe) project framework and the main differences towards CERTS (USA) project framework. In [13] are presented the different electricity market designs in use today: Pool, Bilateral Contracts and the combination of both. In addition to the conventional electricity markets this project covers also the reserve markets, fundamental when dealing with RESs and their uncertainty and variability.

2.2 Energy scheduling

The MGs and VPPs market is predicted to increase 4000MW in capacity between 2017 and 2020 [3]. The growing penetration of DG, allied with the RES uncertainty generation, makes scheduling them in a power system a fundamental task [14]. In literature, the most common aspects of the energy scheduling problem for MGs and VPPs are:

- Formulation type and objective function;
- Solving method;
- Uncertainty (relatable to RES, load, price, etc.);
- Demand response;
- Reactive power;
- Emissions.

Taking into account aforementioned aspects of the scheduling problem, there is literature that shows a suitable perspective for readers to select the best methods based on advantages to schedule the DERs in the power system [15], are detailed in the following of this section.

2.2.1 Energy scheduling problem associated with formulation type and objective function

In a MG the EMS collects information about the electricity market, load and DGs forecast, consumer preferences. Based on that data, does the energy and reserve scheduling (how much power to buy and whom to buy) [15]. In a VPP the aggregator provides the power production profile based on the negotiations with the producers taking into account their expected production forecast [15].

There are several approaches to do the optimization for MGs considering the formulation type and the most common ones in the literature are based on: linear programming [16, 17, 18, 19]; non-linear programming [20]; mixed integer linear programming [21, 22, 23, 24, 25, 26, 27, 28, 29]; mixed integer non-linear programming [30, 31, 32, 33, 34]; quadratic programming [35, 36] and constrained linear least-squares programming [37]. For VPPs, the formulation type can be based on: linear programming [38, 39, 40, 41, 42, 43]; non-linear programming [44]; mixed integer linear programming [45, 46, 47, 48, 49, 50, 51, 52, 53, 54, 55]; mixed integer non-linear programming [56, 57, 58];dynamic programming [59] and quadratic programming [60].

The mixed integer linear programming is the most common class of formulation type used in literature to model the energy scheduling problem in both MGs and VPPs. It's has simplicity as the biggest advantage, however it only admits linear, continuous and integer variables, so when the problem is nonlinear, mathematic relaxation techniques need to be used to convert it into a mixed integer linear problem. Some of those relaxation techniques are presented in [26, 27, 53, 61, 62, 63].

One of the main objectives of a MG is providing power to the consumers at the minimum cost of production, so normally, for MGs, the objective function is cost minimization. The main objective of a VPP is to maximize its profit, so, for VPPs, the objective function is the profit maximization. However, other objective functions can also be a priority, minimization of the emissions for example.

Most computational optimization methods have focused on solving single-objective energy scheduling problems. However, there are a large number of applications that require the simultaneous optimization of several objectives which are often in conflict, and to face this challenge, some authors have proposed multi-objective algorithms to solve it [64]. As an example, [62] deals with the simultaneous scheduling of electrical vehicles and responsive loads to reduce both operation cost and emission in presence of wind and PV powers in MGs. For a more complete information about the energy scheduling problem associated with formulation type and objective function, a table with formulation types and objective functions for a set of problems is highlighted in [15].

2.2.2 Solving methods for the energy scheduling problem

Depending on the modeling of the energy scheduling problem for both MGs and VPPs, the problem can be solved using different solving methods, for example, deterministic, stochastic, iterative or heuristic methods.

More precisely, there are various solving methods within the class of mathematical methods that have been used for solving MGs problems, such as: series and probabilistic methods [65]; convolution method [18]; mesh adaptive direct search [35]; benders decomposition [29, 66]; connection matrix [67]; branch-and-bound algorithm [20]; Lagrangian relaxation decomposition [68]; combinatorial optimization [69]; newton-raphson method [70] and constrained linear least-squares programming [37]. Similarly, the following mathematical methods have been used for VPPs optimization problems, such as: interior point method and primal-dual sub-gradient algorithm [71, 72, 73]; point estimate method [56]; branch-and-bound method [60, 74]; decision Tree [75, 76]; event-driven service-oriented framework [44]; hierarchical structure [77, 78]; game theory [79]; area-based observe and focus algorithm [80] and fuzzy simulation and crisp equivalent [10].

Other class of solving methods are heuristic, these methods can be seen as simple procedures that provide satisfactory and quick solutions to large instances of complex problems rapidly. Meta-heuristics are generalizations of heuristics in the sense that they can be applied to a wide set of problems, needing few modifications to be adapted to a specific case [64]. The main disadvantages of these methods are the optimal solution being associated with estimations and the possible situation related with divergence being more frequent than in mathematical methods. Also, the solution may convert to a local minimum instead of a global one. There are various Heuristic and Meta-Heuristic methods proposed to solve the problem associated with MGs, for example: Particle Swarm Optimization (PSO) [62, 81, 82]; Binary Particle Swarm Optimization (BPSO) [83]; θ-Particle Swarm Optimization (θ-PSO) [84]; Krill Herd Algorithm (KHA) [85]; Teaching–Learning-Based Algorithm (TLBA) [50]; Genetic Algorithm (GA) [86, 87]; Non-dominated Sorting Genetic Algorithm II(NSGA-II) [88, 89]; hybrid algorithm of Lagrangean Relaxation and GA Algorithm (LRGA) [90]; Adaptive Modified Firefly Algorithm(AMFA) [91]; Evolutionary Programming (EP) [92]; Hill Climbing Technique (HC) [92]; Differential Evolution Algorithm(DEA) Accompanied with Fuzzy Technique [76, 93], Competitive Heuristic Algorithm for Scheduling Energy-generation (CHASE) [36] and Habitat Isolation Niche Immune Genetic Algorithm (HINIGA) [94], among others. The heuristic optimization methods addressing the scheduling problem in VPP framework are Multi-Objective Genetic Algorithm [95], GA [96, 97], PSO [98], Accelerated Particle Swarm Optimization (APSO) [99] and Hill Climber and Greedy Randomized Adaptive Search Procedure (GRASP) [100].

In [101], a mathematical mixed integer linear program is formulated and an efficient heuristic approach is designed and subsequently built into a simulated annealing framework to solve the problem.

In some cases, the complexity of the problems to solve is so high that even mathematical or heuristic and meta-heuristic methods are not able to obtain accurate solutions in reasonable runtimes. In these cases parallel processing becomes an interesting alternative [102].

2.2.3 Scheduling problem considering reactive power

In the power system, the reactive power control is one of the main aspects related with the energy scheduling problem. In the distribution system, the reactive power control is essential to ensure the energy delivery with high level of power quality. The DSO is responsible for the active and reactive power flow in the distribution system. Conventionally, the DSO controls the flow of reactive power using static equipment's as capacitor banks and through the reactive power that comes from the upstream connection. Currently and under the smart grid paradigm, the DSO may also be able to acquire active and reactive power from DERs as well as the from local electricity markets to solve potential congestion and voltage problems [103].

In contrast, the MG operator may be able to purchase both active and reactive power requirements to fulfill the needs of its grid. This control, can include static equipment, as well as DER within the MG. In addition, the MG operator must take into account some constraints related to reactive power, as reactive loads in a bus (reactive power output of a unit and reactive load shedding of a bus). In fact, reactive power generation has been commonly used for power loss minimization and voltage profile improvement in power systems. However, the opportunity cost of reactive power generation should be considered since it affects the frequency control capability of the generator to some degree. [104] proposed a distributed nonlinear control based algorithm to achieve the optimal reactive power generation for multiple generators in a power grid.

For a complete review on the reactive power flow parameters and reactive power control, the reader is recommended to consult [15].

2.2.4 Scheduling problem considering emissions

Considering the rising of the environmental concerns over the past years, one of the main objectives of the energy scheduling in a vast set of problems is the minimization of the emissions. Some DERs, especially conventional ones have undesirable impacts on the environment, through the greenhouse gases emitted as a sub product of electricity. For this reason, in the energy scheduling problem, the literature have considered emission as a function that should be minimized. This can be done by maximizing the output of renewable energy. In this section some of these functions are investigated and the type of consideration is explained too [15].

The uncertainty associated with the availability of DER implies an uncertainty in the total emissions produced in a power system. For example, in [62] due to the uncertainty associated with Wind and PV powers, the emission function is formulated in two-stages. In the first-stage, the pollution resulting from the scheduled power generation for load and reserve supplies is calculated. In the second-stage, is calculated the pollution pertaining to the variations of scheduling of the units caused by changes in the behaviors of wind and PV power producers. In this context, an objective function related to the total emissions during the scheduling period is proposed in [31]. In

[105] is quantified the economical impact of DG on pollutant emission cost reduction in the form of a new techno-economic factor. Using this innovative approach would enable system operators to have simultaneous control on network losses and pollutants emission rate of thermal generation unit in the case of deciding to obtain DER economical advantages.

For a complete survey on different emission functions and different types of consideration, the reader is advised to consult [15].

2.2.5 Scheduling problem under uncertainty of DER producers

Current electricity markets designs do not properly cover the uncertain production of RES, mainly PV and wind. In reality, the market follows a sequential and deterministic market design between day-ahead and real-time stages, since the whole information about the future is represented through a single-value forecast at day-ahead stage.

Furthermore, the uncertain renewable production is cleared during the real-time market with penalties for renewable producers that cannot supply the expected forecast established at day-ahead market. In this context, one of the challenges of the current electricity markets is to revise their deterministic market design by adapting advanced tools able to support decision-making under uncertainty. There are several ways to deal with uncertainty such as stochastic programming, robust optimization and optimization using linear decision rules (LDR).

The **stochastic programming** is one of the most used tools to address problems dealing with uncertainty, it has the advantage of modeling problems where uncertainty can happen over different time spans, originating different decision horizons, defining different stages where decisions are taken. The use of stochastic integrated market that co-optimizes day-ahead and balancing stages is a proposed path in the recent literature [106]. However, the performance of such model will heavily depend on the quality of the input information, in this case of the forecast information from renewable production [13]. It is used when the distribution of the error is know.

The **robust optimization** was developed to deal with the worst-case of the uncertainty in optimization problems where the error distribution is not known and is inside an interval. This characteristic makes it ideal to tackle problems with severe uncertainties, thereby based on the worst case analysis and modeled by the Wald's max-min model [107]. This type of optimization returns a feasible solution for all the uncertainty realizations (scenarios) from the uncertainty set and an optimal solution for the worst-case scenario.

The **optimization using LDR** approximates the stochastic programming providing a tractable linear problem at the cost of a potential loss of optimality [108, 109]. It consists in modeling the uncertain decision variable of stochastic model through an affine function. In electric power systems, LDR has been recently used to solve problems in which the uncertainty is modeled by linear functions. In these cases where the objective is obtaining a solution neither optimistic (stochastic approach) neither pessimistic (robust approach), LDR is an alternative [13].

Decision-making under uncertainty in energy planning is essential for the proper functioning of the power system, ensuring suitable levels of system reliability. Thus, the appropriate modelling of the uncertainties in the energy scheduling problem has been studied. More precisely, uncertainties can take the form of power generation and load deviations, market prices, atmospheric conditions, natural catastrophes, etc.

In [22] it is considering uncertainty in EV driving schedule, the author proposes a new EV fleet aggregator model in a stochastic formulation of DER, and it is used an optimization tool to address DER investment and scheduling problems. The objective is to assess the impact of EV interconnections on optimal DER solutions.

Uncertainties generate different scenarios with different parameters, and a problem with a lot of scenarios can be an extremely complex and time consuming process, that is why scenario reduction methods have been used in both MGs and VPPs to make the problem more efficient without compromising the reliability of the results [15]. Some of these methods are detailed in [50, 110].

2.2.6 Scheduling problem considering demand response

The United States Federal Regulatory Commission (FERC) defines Demand Response (DR) as changes in electric usage by demand-side resources from their normal consumption patterns in response to changes in the price of electricity over time, or to incentive payments designed to induce lower electricity use at times of high wholesale market prices or when system reliability is jeopardized. [111]. Loads are encouraged or required to reduce or modify their consumption in benefit of grid operation. For example, demand response programs have been used to shift loads (residential and industrial) away from peak periods [112]. In power systems with high solar penetration there is a major interest in shifting the loads to the daytime period where the solar generation is higher, while shifting other types of generation to other time periods. These programs can be divided in two categories, time based and incentive-based programs. In time-based programs the price of electricity varies according to the supply cost of electricity and there is no incentive or penalty for this type of demand response programs. For instance, in Portugal there are tariffs for the consumers called *tarifa bi-horária and tri-horária and tetra-horária* for industry, in which the prices vary according to the demand in high peak or off-peak periods limited in time intervals. Off-peak hours are nigh time and weekends in which the cost of electricity is lower for the consumers in this demand response program, therefore there is a natural will for shifting the load to these periods [113]. In incentive-based programs there are voluntary programs to curtail without penalties, mandatory programs and programs in which customers can negotiate the amount of load reduction at a negotiated price. This kind of programs are widely used in various scheduling problems, mainly in MGs and VPPs. Interested readers on these types of demand response programs are recommended to check [15].

2.3 Energy and reserve

In addition to the conventional energy markets, ancillary service markets are also essential to the system by ensuring system reliability. These markets are tailored to cope with unforeseen events which may disturb the normal balance of the power system, such as weather-related fluctuations in consumption, short-term changes in major industrial consumption, breakdowns in production facilities, power line outages, and other grid component breakdowns [114].

Ancillary services

FERC defines ancillary services (AS) as "Those services necessary to support the transmission of electric power from seller to purchaser, given the obligations of control areas and transmitting utilities within those control areas, to maintain reliable operations of the interconnected transmission system. Ancillary services supplied with generation include load following, reactive power-voltage regulation, system protective services, loss compensation service, system control, load dispatch services, and energy imbalance services" [115].

In United States, the North American Electric Reliability Corporation (NERC) and/or regional Coordinating Councils, such as the Western Electricity Coordinating Council (WECC) are the entity tasked to establish reliability standards where market operators look for AS from market participants. Winning bids for energy and ancillary services are mutually exclusive, but a generator can receive a compensation for both generation and ancillary service supply in the same period as long as the capacities allocated to each one do not overlap [116].

This section of the project addresses the management of energy and AS in a MG context. As it was referred, in the future there will be more and more RES generating electricity and therefore the uncertainty will increase significantly. It is a good solution to interconnect the energy and reserve to cope with that uncertainty. The following research works present innovative methods for doing the management of energy and AS in a MG.

In [14] is presented a novel stochastic energy and reserve scheduling method for a MG which considers various type of DR programs. In the proposed approach, all types of customers can participate in demand response programs which will be considered in either energy or reserve scheduling. Also, the uncertainties related to renewable DG are modeled by proper probability distribution functions and are managed by reserve provided by both DGs and loads. In [117] is presented a coordinated control strategy for managing the active power reserve in isolated MGs. The methodology can be applied in MGs where a generator assumes the role of the isochronous generator for the overall system. The algorithm evaluates control actions in the on-line environment by solving a constrained dynamic optimization problem which maximizes the overall spinning reserve and, in particular, the reserve offered by the master unit equipped with the isochronous governor controller.

In [118] is proposed a bi–level formulation for a coupled MG power and reserve capacity planning problem, cast within the jurisdiction of a DSO. The upper level problem of the proposed bi–level model minimizes the planning and operational costs of a MG, while the lower level problem ensures reliable power supply by the DSO.

In [119] is used a stochastic model predictive control (SMPC) approach to do the energy management in a MG in the presence of RES where the uncertainties created by this resources are represented by typical scenarios obtained through a two-stage scenario reduction technique and a deterministic finite horizon mixed integer quadratic programming model is formulated based on the selected typical scenarios.

In [120] the author proposes an efficient two-stage stochastic optimal energy and reserve management approach for a MG. It can consider all possible sources and levels of nodal power uncertainties. In the first-stage, the optimal power schedule for possible uncertainties is determined based on the load, wind and solar power forecasts. The actual reserve for the discrepancy between the measured and forecasted data is directly dispatched at second-stage.

In [71] the author considers that operating reserve capacity in a power system is flexible and that one should optimize it by cost-benefit analysis. Based on the reliability evaluation of the generation system, a clearing model of the operating reserve market is proposed to determine the optimal reserve capacity and simultaneously clear the operating reserve market by using a heuristic method. The model is discussed on both uniform-price and pay-as-bid auction mechanisms.

In [96, 97] is addressed the bidding problem faced by a VPP in a joint market of energy and spinning reserve. The proposed bidding strategy is based on the deterministic price-based unit commitment which takes the supply-demand balancing constraint and security constraints of VPP itself into account. The presented model creates a single operating profile from a composite of the parameters characterizing each DER and incorporates network constraints into its description of the capabilities of the portfolio.

Nevertheless of all innovative methods emerged in the scientific community on energy and reserve scheduling of a MG under uncertain renewable production, there is still gaps in the models that are partially covered by this dissertation in the following sections.

Chapter 3

Energy and reserve market model

3.1 Introduction

In the XXI century, the daily problems we face, in areas like finance, transportation, agriculture, engineering, etc. require more and more decision making under uncertainty. Uncertainty has a direct influence on the value of money, fuel prices, raw materials, etc.

Uncertain variables such as environmental conditions, military conflicts and natural catastrophes can have a substantial impact on the prices of products, services and goods. Thus, optimization problems should include uncertain variables that enable decision makers to have complete knowledge of system behaviour, and therefore be prepared for eventual undesirable events. The result is a cost considering all possible scenarios with the associated probability of occurrence (most of the time just the ones with a significant probability, to keep the problem simple) and return the total expected cost.

The optimization problem proposed in this project contemplates the minimization of energy and reserve costs within a MG following a stochastic approach.

3.2 Optimization under uncertainty (two-stage stochastic programming)

Optimization problems under uncertainty are characterized by the need of making decisions before knowing how these decisions will affect the system. In this context several methodologies for solving optimization problems under uncertainty were proposed and this project addresses the two-stage stochastic programming.

The ability to model problems where uncertainty can realize over different decision horizons, thereby defining a number of stages, makes the stochastic programming one of the most used tools to solve problems and find optimal solution in expectation [13].

In a two-stage stochastic programming paradigm, the decision variables of the optimization problem under uncertainty are partitioned into two sets: There are decision variables (x) that must be decided prior to the realization of the contemplated uncertain events, and these variables

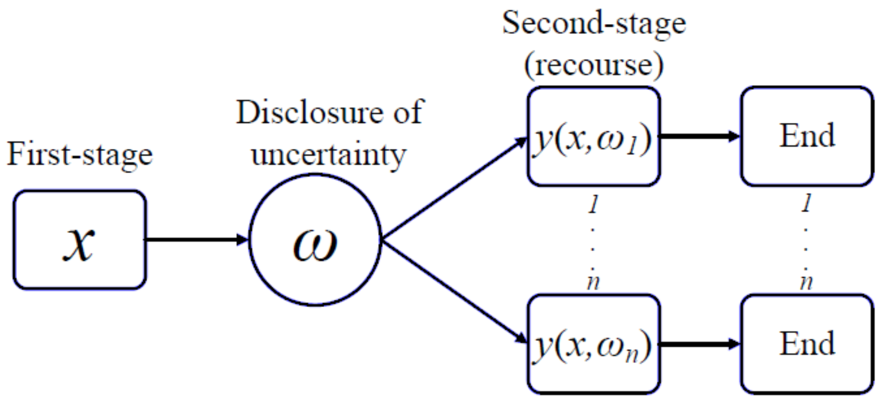

Figure 3.1: Sequence of the decision-making process for the two-stage stochastic programming. Adapted from [121]

compose the first-stage decision variables of the problem. On the other hand, there are stochastic decision variables (y) depending on a set of scenarios (Ω) and are determined after the realization of each scenario (ω) in the second-stage. Consequently, the variables y will also depend on the decision x made in the first-stage. Hence, y can be represented as y(x,ω). Thus, the decision-making process consists of:

1. Make the decision for x;
2. Disclosure of the uncertainty by ω;
3. Make the decision for y(x,ω).

This process is illustrated by figure 3.1 In this context, the two-stage decision making process is summarized as:

- First-stage (here and now). The decision variable x is made before the uncertain event realization;
- Second-stage (wait and see). The decision variable y is made after the uncertain event realization. It depends on a given scenario ω from the set of scenarios Ω.

After the occurrence of the random events, further design or operational policy improvements can be made by selecting the values of the second-stage variables, at a certain cost because, due to uncertainty, the second-stage cost is a random variable. The goal of this project is to find these variables in a way that the total cost of the system is minimized. Thus, the objective of the two-stage stochastic method in this particular case is to choose the first-stage variables so that the sum of the first-stage costs and the expected value of the random second-stage costs is minimized [122]. In this context, the two-stage stochastic programming is used to treat the uncertainty of the

RES in the MG and as a result find the best energy and reserve management of the MG ensuring proper levels of system stability and reliability, taking into consideration the uncertainty modelled in the form of a scenario set. This type of two-stage stochastic problem can be modeled by:

$$\underset{x,y(\omega)}{\text{Min}} \quad C^T x + \sum_{\omega\in\Omega} \pi(\omega) q(\omega)^T y(\omega) \tag{3.1}$$

$$\text{s.t.} \quad Fx = f, \tag{3.2}$$

$$T(\omega)x + H(\omega)y(\omega) = h(\omega), \qquad \forall\omega \tag{3.3}$$

$$x \geq 0, \qquad \forall\omega \tag{3.4}$$

$$y(\omega) \geq 0, \qquad \forall\omega \tag{3.5}$$

To be noted that associated with each scenario is a probability of occurrence $\pi(\omega)$. The function 3.1 minimizes the total cost of both first and second-stages, considering the recourse cost of the second-stage with weighted probability. Additionally, q(ω) stands for the matrix with the costs related to the second-stage decision variable. This problem is subjected to first-stage constraints 3.2 and to constraints that connect the first-stage decision with the recourse decision 3.3. Thus, the first-stage decision affects all the matrixes and vectors of the second-stage [13].

3.3 Optimal Power Flow (OPF) – Benchmark for a DC model

The DC OPF is a linearization of the AC OPF and commonly used as a standard method for considering network behavior in power system problems. In this dissertation the DC OPF is firstly implemented on the energy and reserve scheduling problem in a MG (also called as benchmark model in the remaining of this project), and then further compared to the AC OPF.

The DC model implies a series of simplifications justified by operational considerations under normal operating conditions. These approximations not only linearize the non-linear problem, but also make the problem easier to implement. Some variables are not considered on this formulation type and others disappear as a result of the simplification process. The outcome is a problem with less data that requires less time and processing power to compute.

Approximation to the power flow equations

The AC power-flow equations in a line are the following

$$Pflow^{i,j} = |V_i||V_j|\left(G_{ij}\cos(\theta_i - \theta_j) + B_{ij}\sin(\theta_i - \theta_j)\right) \tag{3.6}$$

$$Qflow^{i,j} = |V_i||V_j|\left(G_{ij}\sin(\theta_i - \theta_j) - B_{ij}\cos(\theta_i - \theta_j)\right) \tag{3.7}$$

There were made simplifications based on the following observations that characterize high voltage transmission lines. For the two-stage stochastic optimization problem using the DC model the reactive part of the power is also not considered.

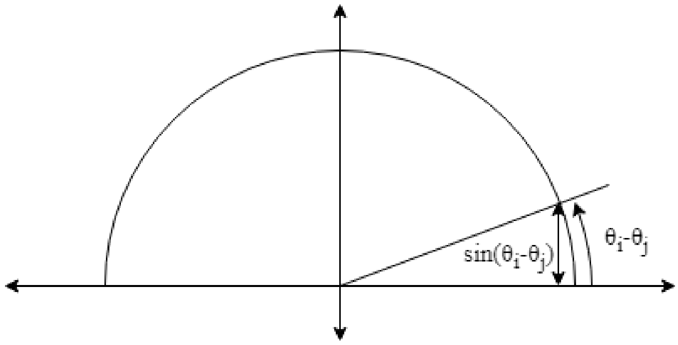

Figure 3.2: Trigonometrical sine function of a small angle.

Observation 1: The resistance of transmission circuits is significantly less than the reactance. Usually, it is the case that the X/R ratio is between 2 and 10. So any given transmission circuit with impedance of $z = r + jx$ will have an admittance of

$$\begin{aligned} & y = \tfrac{1}{z} = \tfrac{1}{r+jx} = \tfrac{1}{r+jx} \times \tfrac{r-jx}{r-jx} = \tfrac{r-jx}{r^2+x^2} \Leftrightarrow \\ & \Leftrightarrow y = \tfrac{r}{r^2+x^2} - \tfrac{jx}{r^2+x^2} = g + jb \end{aligned} \tag{3.8}$$

From the equation above, and considering r«x:

$$g = 0 \quad and \quad b = -\frac{1}{x} \tag{3.9}$$

Hence, the equation 3.6 can be converted into

$$Pflow^{i,j} = |V_i||V_j|\left(B_{ij}\sin(\theta_i - \theta_j)\right) \tag{3.10}$$

Observation 2: In the per-unit system, the numerical values of voltage magnitudes $|V_i|$ and $|V_j|$ are very close to 1.0. The typical range under most operating conditions is located between 0.95 and 1.05 pu., therefore these values can be approximated to 1 and the equation 3.6 can be approximated to:

$$Pflow^{i,j} = B_{ij}\sin(\theta_i - \theta_j) \tag{3.11}$$

Observation 3: For most typical operating conditions, the difference in angles of the voltage phasors at two buses i and j connected by a circuit, which is $\theta_i - \theta_j$ for buses i and j, is very short, so the approximation can be made. This approximation can be better seen in the figure 3.2, where the length of the segments representing the sine of the angle and the angle itself are practically the same. As a result, the active power flow of the active component of the power for a line i,j, given by equation 3.6 is simplified as

$$Pflow^{i,j} = B_{ij} \times (\theta_i - \theta_j) \tag{3.12}$$

3.4 Linear approximation of the ACOPF

AC OPF is a non-convex nonlinear problem difficult to solve when together with other problems, such as the energy and reserve scheduling problem under uncertainty. To improve computational performance and reduce complexity, different linear methods of the AC OPF has emerged. In [61], the author proposes a linear approximation of the AC OPF where functions for active and reactive power flow in a transmission line are introduced, and linear approximation functions for the power triangle equations.

For this linearization, the author considers the observations 2 and 3 of the DC model, however, the observation 2 represents the voltage in a different way. In order to not adulterate the voltage effects on the systems, it is taken into consideration the voltage angle in the reactive power flow. This makes sense because the reactive power flow is influenced by the voltage angle in the buses.

3.4.1 Piecewise linearization of the power-flow equations

In the paper, the author uses the cold start Linear Programming AC (LPAC) model to approximate the power flow equations. Within this scope, equations 3.6 and 3.7 can be approximated by

$$Pflow^{i,j} = G_{ij} - G_{ij}\cos(\theta_i - \theta_j) - B_{ij}(\theta_i - \theta_j) \tag{3.13}$$

$$Qflow^{i,j} = -B_{ij} - G_{ij}(\theta_i - \theta_j) + B_{ij}cos(\theta_i - \theta_j) - B_{ij}(\phi_i - \phi_j) \tag{3.14}$$

where ϕ represents a voltage compensation so that this compensation plus the real bus base voltage should not exceed the defined limits for bus voltage: $|V| \leq |V_n^t| + \phi_n, \forall n \in N$.

To be noted that the cosine function is a nonlinear function which can be linearized. Coffrin et al presents the convex approximation of the cosine function through implementing a piecewise linear function that produces a linear program in the following way [61]. A domain (l,h) must be selected within the range (-π/2,π/2) to ensure convexity. In fact, the angle $\theta_i - \theta_j$ is typically very small and a narrower domain is preferable. Then, a number of s tangent inequalities are placed in the cosine function within the given domain to approximate the convex region. Figure 3.3 illustrates the approximation approach using seven linear inequalities. The dark black line shows the cosine function, the dashed lines are the linear inequality constraints, and the shaded area is the feasible region of the linear system formed by those constraints. The inequalities are obtained from tangents lines at various points on the function.

The convex approximation of the cosine function is given by

$$\begin{aligned} &PWL_{ij(t)} \leq -\sin(a)\left(\theta_{ij(t)} - a\right) + \cos(a) \\ &t \in \{1,\ldots,T\}, \forall i,j \in \{1,\ldots,N_{Bus}\}, a \in \{a_1,\ldots,a_7\}, \theta_{ij(t)} = \theta_{i(t)} - \theta_{j(t)} \end{aligned} \tag{3.15}$$

where α is the tangent point of each segment to the cosine function. In the case of the figure 3.3, the feasible region is under all the 7 equations.

Hence, the equations 3.13 and 3.14 can be approximated by the following linear functions, where PWL is the piecewise linear approximation of the cosine function as shown in [61]. θ is the

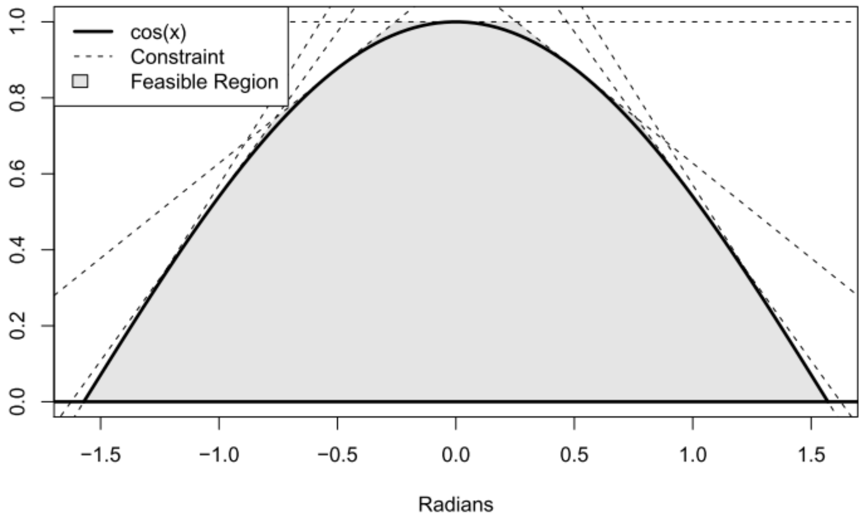

Figure 3.3: Piecewise linearization of the cosine function using 7 inequalities [61]

phase angle on bus i.

$$Pflow_t^{i,j} = G_{ij} - G_{ij}PWL_{ij(t)} - B_{ij}\left(\theta_{ij(t)}\right) \\ t \in \{1,...,T\}, \forall i,j \in \{1,...,N_{Bus}\}, \theta_{ij(t)} = \theta_{i(t)} - \theta_{j(t)} \tag{3.16}$$

$$Qflow_t^{i,j} = -B_{ij} - G_{ij}\theta_{ij(t)} + B_{ij}PWL_{ij(t)} - B_{ij}\phi_{ij(t)} \\ t \in \{1,...,T\}, \forall i,j \in \{1,...,N_{Bus}\}, \theta_{ij(t)} = \theta_{i(t)} - \theta_{j(t)}, \phi_{ij(t)} = \phi_{i(t)} - \phi_{j(t)} \tag{3.17}$$

3.4.2 Piecewise approximation to quadratic equation of power triangle relation

The quadratic power triangle equations relate the active and reactive power production with apparent power

$$S_{DG(dg,t)}{}^2 = P_{DG(dg,t)}^{E}{}^2 + Q_{DG(dg,t)}^{E}{}^2 \tag{3.18}$$

$$S_{DG(dg,t)}^{Min} \leq S_{DG(dg,t)} \leq S_{DG(dg,t)}^{Max}, \quad \forall dg \in \{1,...,N_{DG}\}, \quad \forall t \in \{1,...,T\} \tag{3.19}$$

These equations are valid for both lines and generator and the combination of both can be linearized through a piecewise approximation as proposed in [61]. Hence

$$0 \geq 2Px_{(dg,t,k)}\left(P_{DG(dg,t)}^{E} - Px_{(dg,t,k)}\right) + 2Py_{(dg,t,k)}\left(Q_{DG(dg,t)}^{E} - Py_{(dg,t,k)}\right), \tag{3.20}$$

$$Px_{(dg,t,k)} = S_{DG(dg,t)}^{Max} cos\left(ang_k\right), \tag{3.21}$$

$$Py_{(dg,t,k)} = S_{DG(dg,t)}^{Max} sin\left(ang_k\right), \\ \forall t \in \{1,...,T\}, \forall dg \in \{1,...,N_{DG}\}, \forall k \in \{1,...,N_k\} \tag{3.22}$$

where k is the set for the number of slops of the piecewise function. For a better understanding of these simplifications, the interested readers are referred to [61].

3.5 Energy and reserve market model

3.5.1 Problem description

In this section, it is presented the energy and reserve market model in a MG context.

The modeling of the energy and reserve management problem in a MG environment requires the use of the inherent characteristics of the network. A MG is a small network (distribution system) that can operate in one of two modes: in grid connection or in isolated mode and is composed by small-scale energy resources. Thus, modelling active and reactive energy as well as reserve is essential in distribution systems, especially in systems under strong penetration of renewable resources like MGs.

The MG studied on this project is a medium voltage MG with a substantial penetration of RES, namely PV and Wind, and, as it was explained, these resources imply a high level of uncertainty. To cope with that uncertainty, the scheduling of power reserve to be delivered on the MG when needed is extremely important. There are a large number of events that can affect the generation profiles, and these events are represented by scenarios associated with a certain probability of occurrence. The problem analyses these scenarios and provides the optimal dispatch of energy and reserve which minimizes the total operating costs of the MG.

The problem is modeled as a two-stage stochastic programming model. The objective function minimizes the operation costs of the MG, including both the cost related to the day-ahead energy-reserve dispatch and the expected cost of the anticipated balancing actions to be taken during the real-time operation of the power system. This considering the uncertain power production of DER during the balancing stage. More precisely, the MG operator pretends to optimize the contract of reserve to face the uncertainty of renewable energy resources. This objective function is subject

Minimize Day-ahead dispatch cost + Expected balancing cost

Subject to:

- Day-ahead market constraints:
  - Power balance equations at the day-ahead stage
  - Reserve capacity determination constraints
  - Energy and reserve bids
  - Energy resources limits
  - Line limits
- Real time constraints:
  - Power balance equations at the real-time stage
  - Line limits
  - Activation of reserve determination constraints
- Constrains which relate day-ahead with real time decision variables

Figure 3.4: Optimization process of the two-stage stochastic model

to three different sets of constraints, namely, the constraints involving energy and reserve capacity decision variables in the day-ahead stage, the equations constraining the utilization of balancing resources and which relate day-ahead with real-time decision variables, the constraints declaring the non-negative nature of energy- and reserve-related variables [123]. A generalization of such optimization process is outlined in the figure 3.4.

The model is characterized by optimize the dispatch at the lowest operating cost for the MG. In this way, the MG operator considers the data related with the availability of the generation represented by scenarios as well as network constrains and load demand. Firstly, the problem is modeled through a simplified DC model (DC benchmark) and then the full linearized AC model.

3.5.1.1 DC benchmark model

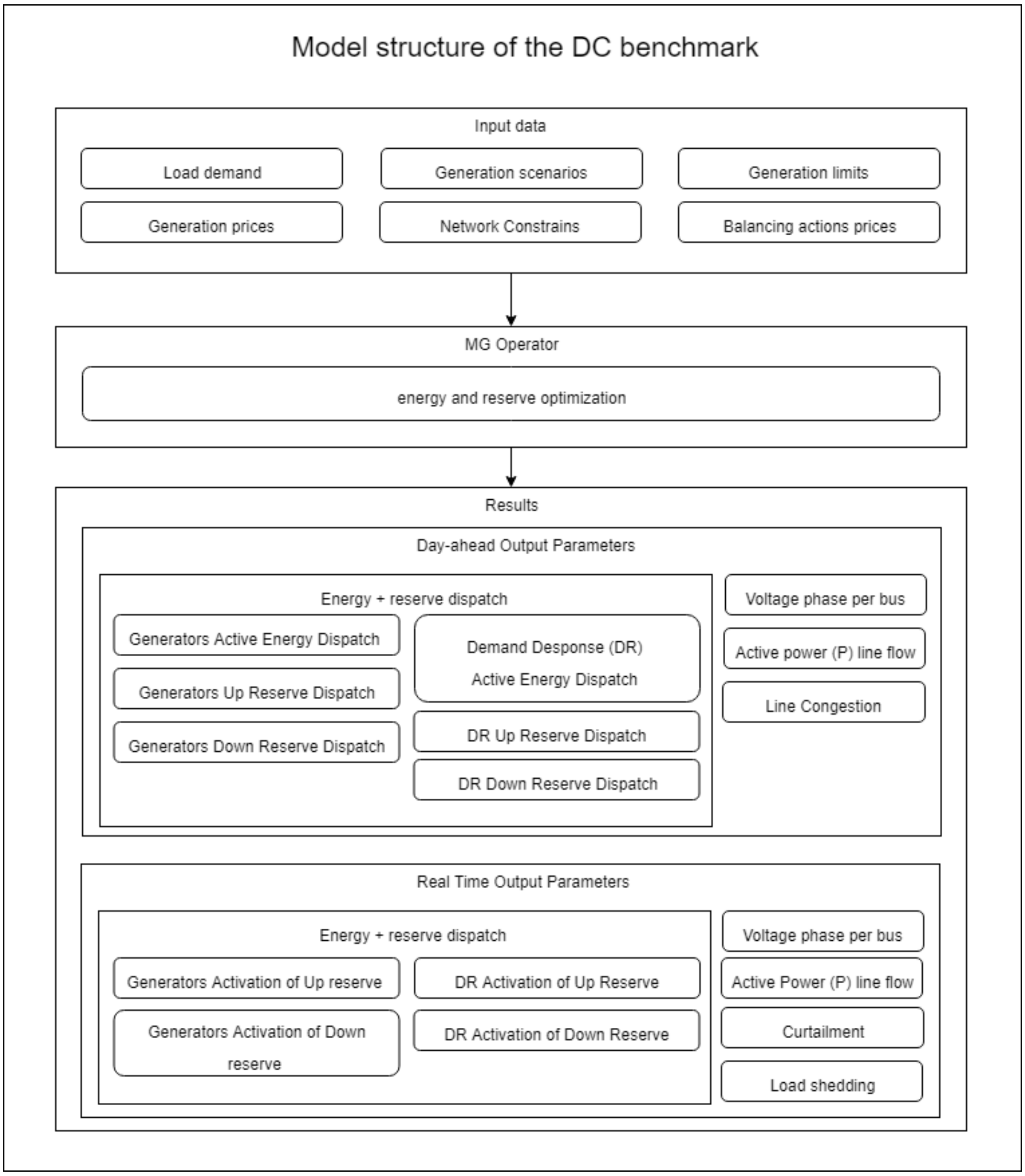

Figure 3.5: Model of the problem considering the DC benchmark

3.5.1.2 Full linearized AC model

The AC linearization model is an evolution of the DC benchmark model, in which the voltage magnitudes and the reactive power are also included, and the power flow equations and power triangle relation are linearized. This model aims to approximate the actual MG behaviour in a more accurate way than the DC benchmark, yet maintaining a full linear system. This AC model can be seen on the figure 3.6.

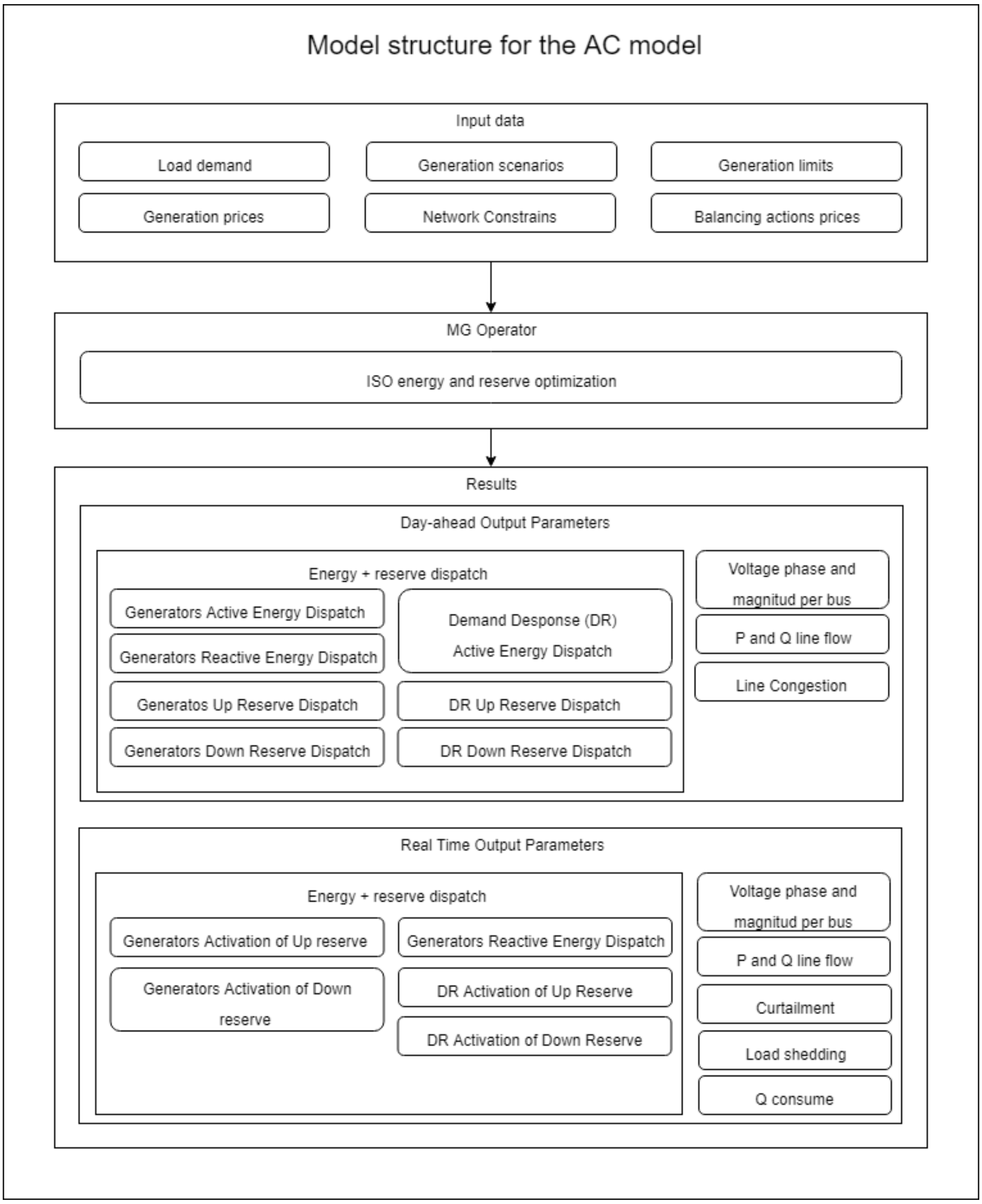

Figure 3.6: Model of the problem considering the full AC linearized model

Looking into the figures 3.5 and 3.6, there is a need to distinguish the two-stage optimization algorithm itself from the remaining phases. This sub-process is illustrated on the figure 3.7. On the first-stage is calculated the optimal dispatch for active and reactive energy, as well as for upward and downward reserve scheduled. Once these values are known, the algorithm proceeds to calculate, for each scenario, the activation of reserve in the second-stage problem and also the reactive energy produced in each scenario.

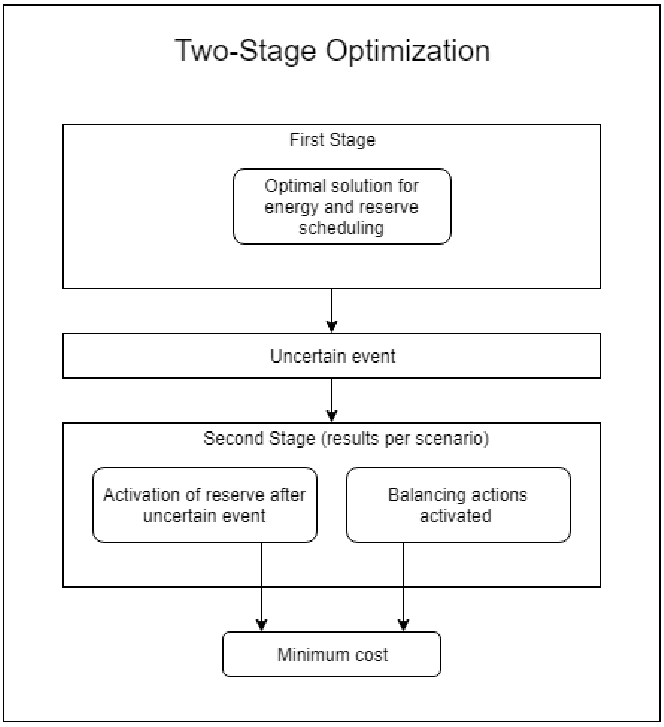

Figure 3.7: Detail of the energy and reserve optimization

3.6 Mathematical formulation

3.6.1 Mathematical formulation for the DC benchmark

Objective Function

The objective function of the optimization problem is modeled into two-stages

$$\min \; F^{DA} + F^{RT} \tag{3.23}$$

where F^{DA} represents the energy and reserve management performed by the MG operator at day-ahead-stage. The matching of energy production and consumption is obtained, and reserve is contracted to eventually be used during real-time operation. This stage comprises energy costs of the energy resources, as well as capacity costs for contracting upward and downward reserve.

$$F_t^{DA} = \sum_{t=1}^{T} \left[\begin{array}{l} \sum_{dg=1}^{N_{DG}} \left(C^{E}_{DG(dg,t)} P^{E}_{DG(dg,t)} + C^{up}_{DG(dg,t)} R^{up}_{DG(dg,t)} + C^{dw}_{DG(dg,t)} R^{dw}_{DG(dg,t)} \right) + \\ \sum_{su=1}^{N_{SU}} \left(C^{E}_{SU(su,t)} P^{E}_{SU(su,t)} + C^{up}_{SU(su,t)} R^{up}_{SU(su,t)} + C^{dw}_{SU(su,t)} R^{dw}_{SU(su,t)} \right) + \\ \sum_{w=1}^{N_{W}} \left(C^{E}_{W(w,t)} \hat{P}^{E}_{W(w,t)} + C^{up}_{W(w,t)} P^{up}_{W(w,t)} + C^{dw}_{W(w,t)} P^{dw}_{W(w,t)} \right) + \\ \sum_{pv=1}^{N_{PV}} \left(C^{E}_{PV(pv,t)} \hat{P}^{E}_{PV(pv,t)} + C^{up}_{PV(pv,t)} P^{up}_{PV(pv,t)} + C^{dw}_{PV(pv,t)} P^{dw}_{PV(pv,t)} \right) + \\ \sum_{l=1}^{N_{L}} \left(C^{E}_{DR(l,t)} P^{E}_{DR(l,t)} + C^{up}_{DR(l,t)} P^{up}_{DR(l,t)} + C^{dw}_{DR(l,t)} P^{dw}_{DR(l,t)} \right) \end{array} \right] \tag{3.24}$$

where, DG, wind, PV and DR are the energy resources available in the MG. In contrast, the activation of the reserve during the real-time stage is given by

$$F_t^{RT} = \sum_{t=1}^{T} \sum_{\omega}^{N_\omega} \pi_\omega \left[\begin{array}{l} \sum_{dg=1}^{N_{DG}} \left[C^{act}_{DG(dg,t)} \left(r^{up}_{DG(dg,t,\omega)} - r^{dw}_{DG(dg,t,\omega)} \right) + C^{cut}_{DG(dg,t)} P^{cut}_{DG(dg,t,\omega)} \right] + \\ \sum_{w=1}^{N_{W}} \left[C^{act}_{W(w,t)} \left(\Delta P_{W(w,t,\omega)} + r^{up}_{W(w,t,\omega)} - r^{dw}_{W(w,t,\omega)} \right) + C^{spill}_{W(w,t)} P^{spill}_{W(w,t,\omega)} \right] + \\ \sum_{pv=1}^{N_{PV}} \left[C^{act}_{PV(pv,t)} \left(\Delta P_{PV(pv,t,\omega)} + r^{up}_{PV(pv,t,\omega)} - r^{dw}_{PV(pv,t,\omega)} \right) + C^{spill}_{PV(pv,t)} P^{spill}_{PV(pv,t,\omega)} \right] + \\ \sum_{l=1}^{N_{L}} \left[C^{act}_{DR(l,t)} \left(r^{up}_{DR(l,t,\omega)} - r^{dw}_{DR(l,t,\omega)} \right) + C^{shed}_{L(l,t)} P^{shed}_{L(l,t,\omega)} \right] \end{array} \right] \tag{3.25}$$

where activation costs for all energy resources are considered. In addition, enforced generation and load curtailment penalties are considered to relax the system in cases insufficient generation for network balance.

The objective function is subject to the following first-stage and second-stage constraints. The first-stage constraints concern all constraints of the problem regarding the day-ahead energy resource scheduling, while the second-stage constraints concern the constraints of the problem during the operating hour, as well as the non-anticipativity constraints.

First-stage constrains

The total power of DG is constrained by

$$P^{E}_{DG(dg,t)} + R^{up}_{DG(dg,t)} \leq P^{Max}_{DG(dg,t)} \qquad , \forall dg \in \{1,...,N_{DG}\}, \forall t \in \{1,...,T\} \tag{3.26}$$

$$P^{E}_{DG(dg,t)} - R^{dw}_{DG(dg,t)} \geq P^{Min}_{DG(dg,t)} \qquad , \forall dg \in \{1,...,N_{DG}\}, \forall t \in \{1,...,T\} \tag{3.27}$$

where energy plus reserve must be within the active power limits of the generator.

In addition, the reserve provision can be constrained by the offers that DG may offer, such as

$$0 \leq R^{up}_{DG(dg,t)} \leq R^{up,Max}_{DG(dg,t)} \qquad ,\forall dg \in \{1,...,N_{DG}\}, \forall t \in \{1,...,T\} \tag{3.28}$$

$$0 \leq R^{dw}_{DG(dg,t)} \leq R^{dw,Max}_{DG(dg,t)} \qquad ,\forall dg \in \{1,...,N_{DG}\}, \forall t \in \{1,...,T\} \tag{3.29}$$

where both upward and downward reserve are constrained by the bid offered by the player in the market. Constraints 3.26 to 3.29 are also applied to external suppliers, wind units, PV units and loads with DR programs. External suppliers are units that represent the power at upstream connections of the grid. The energy produced by wind and PV units is settled by parameter $\hat{P}^{E}_{W(w,t)}$, that is the conditional mean forecast of wind and PV at the day-ahead stage. The active balance equation at day-ahead stage is given by

$$\begin{gathered}\sum_{dg=1}^{N_{DG}} P^{E,i}_{DG(dg,t)} + \sum_{su=1}^{N_{SU}} P^{E,i}_{SU(su,t)} + \sum_{w=1}^{N_W} \hat{P}^{E,i}_{W(w,t)} + \sum_{pv=1}^{N_{PV}} \hat{P}^{E,i}_{PV(pv,t)} + \sum_{l=1}^{N_L} \left(P^{E,i}_{DR(l,t)} - P^{i}_{L(l,t)}\right) - \\ \sum_{j \in N_{bus}}^{i \neq j} Pflow^{i,j}_t = 0 \\ t \in \{1,...,T\}, \forall i,j \in \{1,...,N_{Bus}\}\end{gathered} \tag{3.30}$$

where $Pflow^{i,j}_t$ represents the active power flow on the line ij, which is given by the equation 3.12 explained before.

Second-stage constrains

The second-stage constraints contemplates all the stochastic constraints dependent of scenario ω. The activation of upward and downward reserve for DG units is limited by the upward and downward offer contracted in the first-stage, respectively. In parallel, the generation curtailment power is constrained by the difference between the current operating point and the downward offer of the DG unit, hence

$$r^{up}_{DG(dg,t,\omega)} \leq R^{up}_{DG(dg,t)}, \quad \forall dg \in \{1,...,N_{DG}\}, \forall t \in \{1,...,T\}, \forall \omega \in \{1,...,N_\omega\} \tag{3.31}$$

$$r^{dw}_{DG(dg,t,\omega)} \leq R^{dw}_{DG(dg,t)}, \quad \forall dg \in \{1,...,N_{DG}\}, \forall t \in \{1,...,T\}, \forall \omega \in \{1,...,N_\omega\} \tag{3.32}$$

$$P^{cut}_{DG(dg,t,\omega)} \leq P^{E}_{DG(dg,t)} - r^{dw}_{DG(dg,t,\omega)}, \forall dg \in \{1,...,N_{DG}\}, \forall t \in \{1,...,T\}, \forall \omega \in \{1,...,N_\omega\} \tag{3.33}$$

When the capacity of the line is not enough to transmit the desire amount of power, there is a need to curtail generation at a certain cost and that curtailment or spillage is represented by P^{cut}_{DG}, P^{spill}_{PV} or P^{spill}_{W} depending on the generator. Similarly, the equations 3.31 and 3.32 are valid for wind and PV producers and the activation of spillage is given by

$$\begin{gathered}P^{spill}_{W(w,t,\omega)} \leq \hat{P}^{E}_{W(w,t)} - r^{dw}_{W(w,t,\omega)} + \Delta P_{W(w,t,\omega)}, \\ \forall w \in \{1,...,N_W\}, \forall t \in \{1,...,T\}, \forall \omega \in \{1,...,N_\omega\}\end{gathered} \tag{3.34}$$

where ΔP is the wind power deviation in each scenario ω. This is, the uncertainty around wind power production. This parameter is applied only to RES, such as wind and PV. In contrast, the activation of upward and downward DR offers are constrained by

$$r^{up}_{DR(l,t,\omega)} \leq R^{up}_{DR(l,t)}, \forall l \in \{1,...,N_L\}, \forall t \in \{1,...,T\}, \forall \omega \in \{1,...,N_\omega\} \tag{3.35}$$

$$r^{dw}_{DR(l,t,\omega)} \leq R^{dw}_{DR(l,t)}, \forall l \in \{1,...,N_L\}, \forall t \in \{1,...,T\}, \forall \omega \in \{1,...,N_\omega\} \tag{3.36}$$

$$\begin{aligned} &P^{shed}_{L(l,t,\omega)} \leq P_{L(l,t)} - P^{E}_{DR(l,t)} - r^{up}_{DR(l,t,\omega)} \\ &\forall l \in \{1,...,N_L\}, \forall t \in \{1,...,T\}, \forall \omega \in \{1,...,N_\omega\} \end{aligned} \tag{3.37}$$

Alternatively, to cut down generation when the capacity of the line is not enough to transmit the desire amount of power, the load can also be cut at a certain cost, this is called load shedding and is represented above by P^{shed}_{L}. The network balancing on the second-stage problem is formulated as

$$\begin{aligned} &\sum_{dg=1}^{N_{DG}} \left(P^{E,i}_{DG(dg,t)} + r^{up,i}_{DG(dg,t,\omega)} - r^{up,i}_{DG(dg,t,\omega)} - P^{cut,i}_{DG(dg,t,\omega)}\right) + \\ &\sum_{su=1}^{N_{SU}} \left(P^{E,i}_{SU(su,t)} + r^{up,i}_{SU(su,t,\omega)} - r^{up,i}_{SU(su,t,\omega)} - P^{cut,i}_{SU(su,t,\omega)}\right) + \\ &\sum_{w=1}^{N_{W}} \left(\hat{P}^{E,i}_{W(w,t)} + \Delta P^{i}_{W(w,t,\omega)} + r^{up,i}_{W(w,t,\omega)} - r^{up,i}_{W(w,t,\omega)} - P^{spill,i}_{W(w,t,\omega)}\right) + \\ &\sum_{pv=1}^{N_{PV}} \left(\hat{P}^{E,i}_{PV(pv,t)} + \Delta P^{i}_{PV(pv,t,\omega)} + r^{up,i}_{PV(pv,t,\omega)} - r^{up,i}_{PV(pv,t,\omega)} - P^{spill,i}_{PV(pv,t,\omega)}\right) + \\ &\sum_{l=1}^{N_{L}} \left(P^{E,i}_{DR(l,t)} + r^{up,i}_{DR(l,t,\omega)} - r^{dw,i}_{DR(l,t,\omega)} + P^{Shed,i}_{L(l,t,\omega)} - P^{i}_{L(l,t)}\right) - \sum_{j \in N_{bus}}^{i \neq j} Pflow^{RT,i,j}_{(t,\omega)} = 0 \\ &t \in \{1,...,T\}, \forall i,j \in \{1,...,N_{Bus}\}, \omega \in \{1,...,N_\omega\} \end{aligned} \tag{3.38}$$

where $Pflow^{RT,i,j}_{(t,\omega)}$ represents the active injected power for each scenario ω. In a similar way as in equation 3.12, is given for this case by

$$\begin{aligned} &Pflow^{RT,i,j}_{(t,\omega)} = B_{ij}\left(\theta_{ij(t,\omega)}\right) \\ &t \in \{1,...,T\}, \forall i,j \in \{1,...,N_{Bus}\}, \omega \in \{1,...,N_\omega\}, \theta_{ij(t)} = \theta_{i(t)} - \theta_{j(t)} \end{aligned} \tag{3.39}$$

3.6.2 Mathematical formulation for the linearized AC model

The full modeling of an AC OPF can be very hard to compute when considering complex problems such as the energy and reserve management under uncertainty. In this way, a linear-programming approximation of the AC OPF proposed by [61] is implemented. This approximation technique takes into account both active and reactive power features of the network. Comparing with the DC model, the linearized AC model has extra constrains and constrains which better approximate the nonlinear behaviour of the system. This extra constrains are detailed in the following of the this section.

Objective Function

$$F_t^{DA} = \sum_{t=1}^{T} \begin{bmatrix} \sum_{dg=1}^{N_{DG}} \left(C^{E}_{DG(dg,t)} P^{E}_{DG(dg,t)} + C^{up}_{DG(dg,t)} R^{up}_{DG(dg,t)} + C^{dw}_{DG(dg,t)} R^{dw}_{DG(dg,t)} \right) + \\ \sum_{su=1}^{N_{SU}} \left(C^{E}_{SU(su,t)} P^{E}_{SU(su,t)} + C^{up}_{SU(su,t)} R^{up}_{SU(su,t)} + C^{dw}_{SU(su,t)} R^{dw}_{SU(su,t)} \right) + \\ \sum_{w=1}^{N_{W}} \left(C^{E}_{W(w,t)} \hat{P}^{E}_{W(w,t)} + C^{up}_{W(w,t)} P^{up}_{W(w,t)} + C^{dw}_{W(w,t)} P^{dw}_{W(w,t)} \right) + \\ \sum_{pv=1}^{N_{PV}} \left(C^{E}_{PV(pv,t)} \hat{P}^{E}_{PV(pv,t)} + C^{up}_{PV(pv,t)} P^{up}_{PV(pv,t)} + C^{dw}_{PV(pv,t)} P^{dw}_{PV(pv,t)} \right) + \\ \sum_{l=1}^{N_{L}} \left(C^{E}_{DR(l,t)} P^{E}_{DR(l,t)} + C^{up}_{DR(l,t)} P^{up}_{DR(l,t)} + C^{dw}_{DR(l,t)} P^{dw}_{DR(l,t)} \right) - \\ \sum penalty \times PWL_{ij} \end{bmatrix} \tag{3.40}$$

The piecewise approximation of the cosine function needs to be maximized to make it as close as possible to the true cosine value. This is done by adding this parameter to the objective function (multiplied by -1 because the the objective function is a minimization function). There is also a need to add a convergence penalty to make the solution feasible. This penalty depends on the problem data, but typically needs to be a large value in order to maximize the PWL value.

The penalty value needs to be carefully selected and tested for each problem because the PWL function is very sensitive and a small variation on the penalty can easily compromise the results.

$$F_t^{RT} = \sum_{t=1}^{T} \sum_{\omega}^{N_\omega} \pi_\omega \begin{bmatrix} \sum_{dg=1}^{N_{DG}} \left[C^{act}_{DG(dg,t)} \left(r^{up}_{DG(dg,t,\omega)} - r^{dw}_{DG(dg,t,\omega)} \right) + C^{cut}_{DG(dg,t)} P^{cut}_{DG(dg,t,\omega)} \right] + \\ \sum_{w=1}^{N_{W}} \left[C^{act}_{W(w,t)} \left(\Delta P_{W(w,t,\omega)} + r^{up}_{W(w,t,\omega)} - r^{dw}_{W(w,t,\omega)} \right) + C^{spill}_{W(w,t)} P^{spill}_{W(w,t,\omega)} \right] + \\ \sum_{pv=1}^{N_{PV}} \left[C^{act}_{PV(pv,t)} \left(\Delta P_{PV(pv,t,\omega)} + r^{up}_{PV(pv,t,\omega)} - r^{dw}_{PV(pv,t,\omega)} \right) + C^{spill}_{PV(pv,t)} P^{spill}_{PV(pv,t,\omega)} \right] + \\ \sum_{l=1}^{N_{L}} \left[C^{act}_{DR(l,t)} \left(r^{up}_{DR(l,t,\omega)} - r^{dw}_{DR(l,t,\omega)} \right) + C^{shed}_{L(l,t)} P^{shed}_{L(l,t,\omega)} \right] - \\ \sum penalty \times PWL_{ij} \end{bmatrix} \tag{3.41}$$

First-stage constrains

Similarly, to the active power, the reactive power production is constrained by its minimum and maximum thresholds as

$$Q^{Min}_{DG(dg,t)} \leq Q^{E}_{DG(dg,t)} \leq Q^{Max}_{DG(dg,t)} \qquad , \forall dg \in \{1,...,N_{DG}\}, \forall t \in \{1,...,T\} \tag{3.42}$$

The power triangle relates active and reactive power production with apparent power by the linearized equations 3.20, 3.21 and 3.22 explained in section 3.4.2.

The reactive power consumption of load l with DR program is determined as

$$Q_{L(l,t)} = \left(P_{L(l,t)} - P^{E}_{DR(l,t)}\right) \tan\phi \qquad ,\forall l \in \{1,...,N_L\}, \forall t \in \{1,...,T\} \tag{3.43}$$

The ϕ was considered 0,3.

The active balance equation at day-ahead stage is given by the equation 3.30 but the power flow is now given by the equation 3.16 shown in the section 3.4.1.

In parallel, the reactive power balance refers to the reactive power generation and consumption in the system and is modelled as

$$\begin{aligned}&\sum_{dg=1}^{N_{DG}} Q^{E,i}_{DG(dg,t)} + \sum_{su=1}^{N_{SU}} Q^{E,i}_{SU(su,t)} + \sum_{w=1}^{N_{W}} Q^{E,i}_{W(w,t)} + \sum_{pv=1}^{N_{PV}} Q^{E,i}_{PV(pv,t)} - \sum_{l=1}^{N_{L}} \left(Q^{i}_{L(l,t)}\right) - \sum_{j\in N_{bus}}^{i\neq j} Qflow^{i,j}_{t} = 0 \\ &t \in \{1,...,T\}, \forall i,j \in \{1,...,N_{Bus}\}\end{aligned} \tag{3.44}$$

where $Qflow^{i,j}_{t}$ represents the reactive power flow in the line ij in time t system, which is modelled as explained before by the equation 3.17 shown in section 3.4.1.

The voltage in each bus is limited by the upward and downward bound as

$$V^{i}_{Min} \leq V_{i(t)} \leq V^{i}_{Max} \qquad ,\forall t \in \{1,...,T\}, \forall i,j \in \{1,...,N_B\} \tag{3.45}$$

in which $V_{i(t)}$ is the base voltage of the bus (considered equal 1) plus the voltage compensation, $|V_{i(t)}| \leq 1 + \phi_{i(t)}, \forall n \in N$, therefore:

$$V^{i}_{Min} \leq 1 + \phi_{i(t)} \leq V^{i}_{Max} \qquad ,\forall t \in \{1,...,T\}, \forall i,j \in \{1,...,N_B\} \tag{3.46}$$

The thermal line limit is modeled once again through the quadratic equation of power triangle, on 3.20, 3.21 and 3.22.

Second-stage constrains

The reactive power production of DG units is constrained by the minimum and maximum limits as:

$$Q^{Min}_{DG(dg,t)} \leq Q^{RT}_{DG(dg,t,\omega)} \leq Q^{Max}_{DG(dg,t)} \quad ,\forall dg \in \{1,...,N_{DG}\}, \forall t \in \{1,...,T\}, \forall \omega \in \{1,...,N_\omega\} \tag{3.47}$$

The reactive power consumption by scenario is thereby constrained by

$$\begin{aligned}&Q^{RT}_{L(l,t,\omega)} = \left(P_{L(l,t)} - P^{E}_{DR(l,t)} + r^{dw}_{DR(l,t,\omega)} - r^{up}_{DR(l,t,\omega)} - P^{Shed}_{L(l,t,\omega)}\right) \tan\phi \\ &\forall l \in \{1,...,N_L\}, \forall t \in \{1,...,T\}, \forall \omega \in \{1,...,N_\omega\}\end{aligned} \tag{3.48}$$

Once again ϕ =0.3.

The network balancing on the second-stage problem is given by the formulation of the AC linearization also applied in the first-stage problem, but now considering the variables of the second-constraint problem. Thus, the active power balancing is formulated by the equation 3.38 as on the DC model, but the power flow is calculated through the equation

$$\begin{aligned}&Pflow_{(t,\omega)}^{RT,i,j} = G_{ij} - G_{ij}PWL_{ij(t,\omega)} - B_{ij}\left(\theta_{ij(t,\omega)}\right)\\&t \in \{1,...,T\}, \forall i,j \in \{1,...,N_{Bus}\}, \omega \in \{1,...,N_{\omega}\}, \theta_{ij(t)} = \theta_{i(t)} - \theta_{j(t)}\end{aligned} \tag{3.49}$$

In parallel, the reactive power balance refers to the reactive power generation and consumption in the system for each scenario ω and is modelled as

$$\begin{aligned}&\sum_{dg=1}^{N_{DG}} Q_{DG(dg,t,\omega)}^{RT,i} + \sum_{su=1}^{N_{SU}} Q_{SU(su,t,\omega)}^{RT,i} + \sum_{w=1}^{N_{W}} Q_{W(w,t,\omega)}^{RT,i} + \sum_{pv=1}^{N_{PV}} Q_{PV(pv,t,\omega)}^{RT,i} -\\&\sum_{l=1}^{N_L}\left(Q_{L(l,t)}^{RT,i}\right) - \sum_{j\in N_{bus}}^{i\neq j} Qflow_{(t,\omega)}^{RT,i,j} = 0\\&t \in \{1,...,T\}, \forall i,j \in \{1,...,N_{Bus}\}, t \in \{1,...,N_{\omega}\}\end{aligned} \tag{3.50}$$

where $Qflow_{(t,\omega)}^{RT,i,j}$ represents the reactive injected power in the system for each scenario ω. which is modelled in a similar way as for the first-stage by the equation

$$\begin{aligned}&Qflow_{t}^{RT,i,j} = -B_{ij} - G_{ij}\theta_{ij(t,\omega)} + B_{ij}PWL_{ij(t,\omega)} - B_{ij}\phi_{ij(t,\omega)}\\&t \in \{1,...,T\}, \forall i,j \in \{1,...,N_{Bus}\}, \omega \in \{1,...,N_{\omega}\}, \theta_{ij(t)} = \theta_{i(t)} - \theta_{j(t)}, \phi_{ij(t)} = \phi_{i(t)} - \phi_{j(t)}\end{aligned} \tag{3.51}$$

The voltage in each bus is limited by the upward and downward bound as

$$V_{Min}^{i} \leq 1 + \phi_{i(t,\omega)} \leq V_{Max}^{i} \qquad , \forall t \in \{1,...,T\}, \forall \omega \in \{1,...,N\omega\}, \forall i,j \in \{1,...,N_B\} \tag{3.52}$$

Finally, the thermal line limit is modeled through the quadratic equations of power triangle 3.20, 3.21 and 3.22.

Chapter 4

Assessment of energy and reserve management model (case study)

4.1 Introduction

In this chapter is presented the case study illustrating the application of the simulation of the two-stage stochastic programming model proposed in the previous chapter under the MG context. This case study was selected to cover a diversity of situations of the involved players in the MG, and therefore test and validated the proposed models. The results obtained are presented and discussed and some general conclusions are made.

4.2 Case study

The case study refers to a joint market model for energy and reserve in a MG. It is used the two-stage stochastic optimization to obtain the optimal dispatch for energy and upward and downward reserve in the MG. The main objective of this model is the minimization of the market costs for the MG operator.

On a first phase of the work it was done the two-stage optimization program applied to a DC model detailed on the chapter 3 of this project. After that, the results were analyzed and the veracity of the optimal solution was tested using two quality metrics detailed on [124], namely the Expected Value of Perfect Information (EVPI) and the Value of the Stochastic Solution (VSS) to be further discussed. Once the results for the DC benchmark were satisfactory, the AC Model was tested and the results for this model were collected and analyzed.

4.3 Outline

This subsection includes an outline of the problem, as well as, the input data necessary for the simulation of the models. The results are reported together with some conclusions related to the problem.

The initial two-stage problem was meant to provide a solution for 100 different scenarios with the same probability of realization throughout 24 time periods, but due to the high complexity of the problem and computer limitations, the number of scenarios for the AC model was cut down to 10 and the optimization was done separately 24 times, each one for each time period not dependent from each other. The DC model was simulated for the same conditions but because it is a less complex problem with less data it was possible to test it for 10, 50 and 100 scenarios. This was done to evaluate possible impacts of the number of scenarios on the final results.

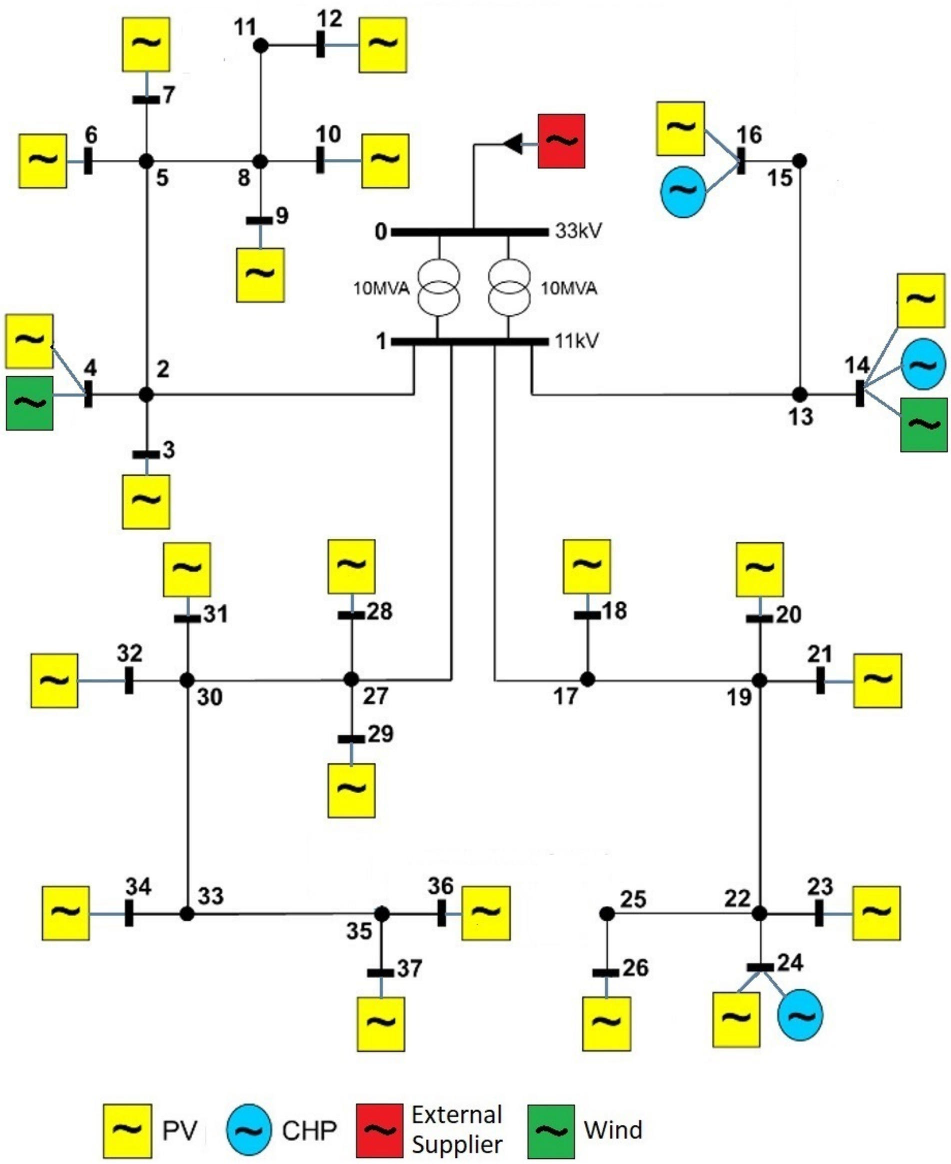

Figure 4.1: 37-bus distribution grid - MG adapted from [125].

The computations were carried out with dual-simplex as an LP solver on an Intel Core i7 2.40 GHz processor with 4GB RAM. All modeling was performed in MATLAB modeling language.

The original distribution network is presented in [125], while the energy mix in 2050 used for updating the network is proposed in [126]. The simulation runs for a 11kV MV MG, at the distribution level, with 37 buses, 22 loads, 28 aggregators and 36 distribution lines. The design of the MG is shown on the figure 4.1 and is composed by:

- 1 external supplier representing the upstream connection with the 33kV MV line.
- 3 CHP aggregators
- 2 Wind aggregators
- 22 PV aggregators

For a given time period in the future, the system operator must determine here-and-now both the energy dispatch and the reserve capacity needs. Naturally, reserve capacity is required to cope with the uncertain wind and PV power production, which is represented via scenarios, with the same probability of occurrence. Specifically, the sequence of decisions that the system operator has to face is as follows:

1. Determine the production levels of DG units and the allocation of reserves to deal with the uncertain wind and PV power production;
2. Deployment of reserve in the form of balancing energy during the real-time operation of the power system to accommodate the actual realization of wind and PV power production. Four different types of balancing actions can be undertaken for this purpose, namely
   (a) The power output of the generator unit g can be increased from P to $P+r^{up}$, where r^{up} is the balancing energy obtained from the upward reserve capacity of unit i, denoted as R^{up}. This action entails a cost given by $C^{act}r^{up}$, where C^{act} is the marginal production cost declared by unit g (g can be DG, PV or wind);
   (b) Conversely, the power output of unit i can be decreased from P to $P-r^{dw}$, where r^{dw} is the balancing energy resulting from the deployment of the downward reserve capacity of unit i, represented by R^{dw} . This action implies cost savings of $C^{act}r^{dw}$;
   (c) A part of the production, P^{cut} (or P^{spill} in the case of wind generators) can be curtailed (spilled) with the cost C^{cut} (C^{spill});
   (d) A part of the load l, P_L^{shed} , can be also curtailed. This action involves, though, the so-called value of lost load associated with the cost C_L^{shed}.

The following tables contain relevant input data about the general characteristics of the DER and consumers. They also show the unit prices for energy and reserve as well as for the contingency balancing actions.

Table 4.1: General characteristics and operating point for DER.

DER	Number of units	Total power installed	Operating point Max	Mean	Min
External Supplier	1	20 (MVA)	19.61 (MW)	10.68 (MW)	5.64 (MW)
CHP	3	1.5 (MVA)	1.21 (MW)	1.04 (MW)	0.74 (MW)
Wind	2	2.5 (MW)	1.91 (MW)	1.77 (MW)	1.45 (MW)
PV	22	7.74 (MW)	5.55 (MW)	1.96 (MW)	0 (MW)
DR	22	0.68 (MW)	0.1 (MW)	0.03 (MW)	0 (MW)

Table 4.2: Consumers characteristics

Load	Bus	Active power consumption (MW) Max	Mean	Min
1	3	1.1905	0.3732	0.6779
2	4	1.0156	0.2061	0.5912
3	6	1.0298	0.0884	0.5990
4	7	1.2591	0.3947	0.7169
5	9	1.0890	0.5390	0.7618
6	10	1.0409	0.2987	0.6366
7	12	1.0301	0.3230	0.5865
8	14	1.9074	0.3870	1.1104
9	16	2.5983	0.7456	1.5891
10	18	1.0298	0.5097	0.7203
11	20	1.0298	0.0884	0.5990
12	21	1.1905	0.3732	0.6779
13	23	1.2723	0.3651	0.7781
14	24	1.0890	0.5390	0.7618
15	26	1.0301	0.3230	0.5865
16	28	0.8788	0.1783	0.5116
17	29	0.8662	0.0744	0.5038
18	31	1.0014	0.3140	0.5702
19	32	1.0119	0.2904	0.6189
20	34	1.0890	0.0935	0.6334
21	36	1.0741	0.2179	0.6253
22	37	1.0301	0.3230	0.5865

Table 4.3: DER energy and reserve cost

DER	Energy cost (m.u./kWh)			Upward reserve cost (m.u./kWh)			Downward reserve cost (m.u./kWh)		
	Max	Mean	Min	Max	Mean	Min	Max	Mean	Min
External supplier	-	0.05	-	-	0.25	-	-	0.15	-
CHP	0.03	0.02	0.01	0.15	0.10	0.05	0.09	0.06	0.03
Wind	-	0	-	-	0.10	-	-	0.01	-
PV	-	0	-	-	0.10	-	-	0.01	-
DR	-	0.15	-	-	0.18	-	-	0.165	-

Table 4.4: Cost of the contingency balancing actions

DER	Curtailment / Spillage / Load shedding (m.u./kWh)		
	Max	Mean	Min
External Supplier	-	1	-
CHP	-	2	-
Wind	-	0.5	-
PV	-	0.5	-
DR	-	0.15	-

4.4 Results

4.4.1 Benchmark - DC model

The results obtained for the DC model are shown throughout this section. They are represented by color-coded diagrams, the purple colour represents the external supplier, the blue represents the CHP generators, the green represents the wind, the yellow represents the PV and the red represents the DR. The results are presented for 10, 50 and 100 scenarios:

In the figures 4.2, 4.3 and 4.4 are presented the results obtained from the simulation of the DC model for 10, 50 and 100 scenarios.

As it can be seen by the figure 4.2, the active power produced does not have a significant variance when moving from 10 to 50 or 100 scenarios considered. The wind and CHP generation is practically constant throughout all day in the three cases. During the night and the first hours of the morning there is no PV generation. The PV and wind follows a feed-in tariff, so they have not generation cost for energy. In contrast, CHP and the external supplier have a significant cost, being the CHP cheaper than the external supplier. This was done to make all the generation from RES dispatchable and make the MG more independent from the grid, despite of that the external supplier provides the majority of the energy to the consumers, particularly during the night and the first hours of the morning.

In the figure 4.3 it is shown the results for the scheduled upward reserve on the day-ahead stage. By the analysis of the figure 4.2 it is obvious that during the morning and afternoon there is more PV generation, and therefore more uncertainty. To cope with this higher level of uncertainty, the MG schedules more upward reserve during the referred period. This reserve was assured by wind, PV and CHP. Its possible to spot differences when moving from 10 to 50 or 100 scenarios, more scenarios mean more uncertain events to be considered, so the diagrams of the upward reserve for 50 and 100 scenarios are wider, that means there is more reserve being scheduled during larger time periods.

The figure 4.4 shows the downward reserve scheduled on the day-ahead stage and as it can be seen it is (by the same reason as the upward reserve) higher during the afternoon, although not as high as the upward reserve and it was assured only by wind and PV generators. There is no significant difference in the amount of reserve scheduled on the three cases, but when considering 50 and 100 scenarios, there is more reserve scheduled from wind and less from PV units comparing with the case of 10 scenarios. Another conclusion of this DC model dispatch is that there was:

- no activation of the contingency balancing actions of curtailment or load shedding;
- no schedule power, upward or downward reserve for the day-ahead stage from the DR;
- no activation of reserve on the real-time stage from the DR.

On the figure 4.5 can be seen the congestion of the lines (in percentage of the line capacity). At purple its presented the average power flow on each line. The filled colored lines represent for each scenario the average power flow, while the red dotted line represents the maximum power flow the line experiences considering all time periods and all scenarios. The main conclusion taken is that no line is overloaded in any circumstance. The congestion for 50 and 100 scenarios provided very similar results, but due to the difficulty of presenting a graphic for a large number of scenarios, only the first case is presented.

After the results, and in order to evaluate the credibility of the stochastic solution, two quality metrics were used to appraise the interest of the two-stage stochastic programming model: EVPI and VSS.

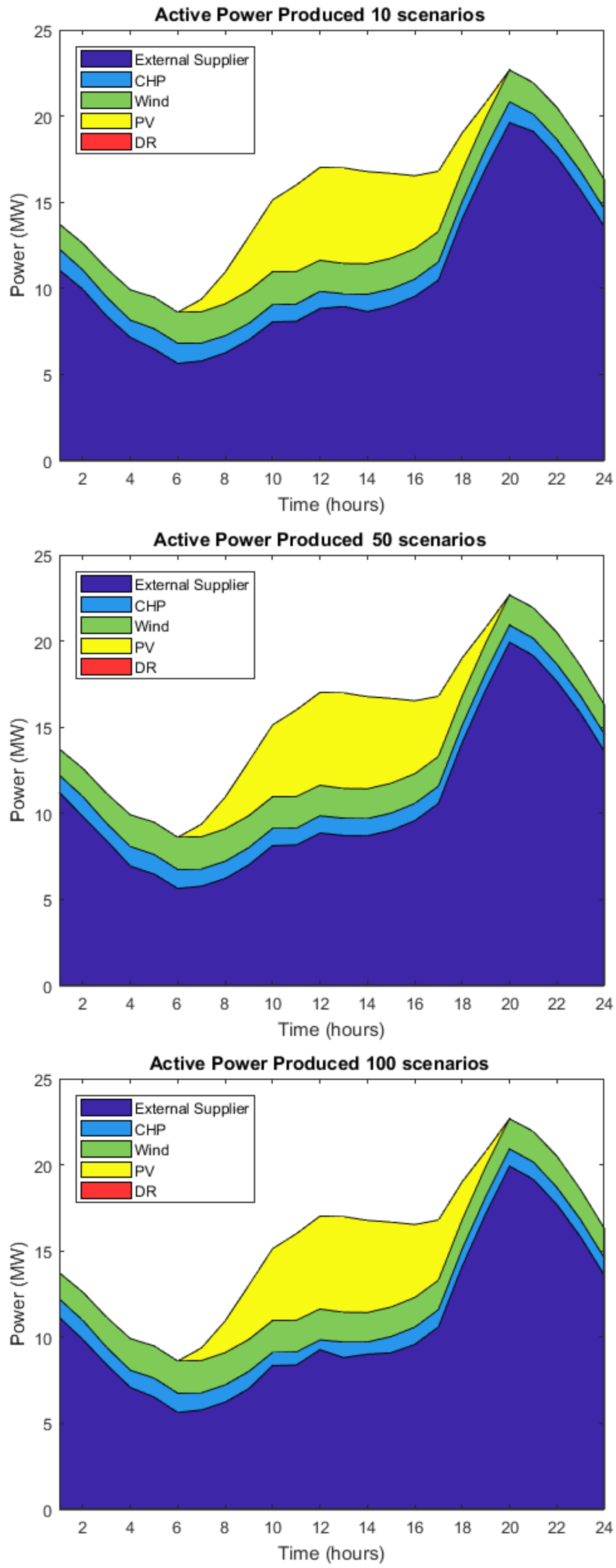

Figure 4.2: Active power delivered on day-ahead stage by each one of the 28 aggregators along the 24-time periods (considering 10, 50 and 100 scenarios).

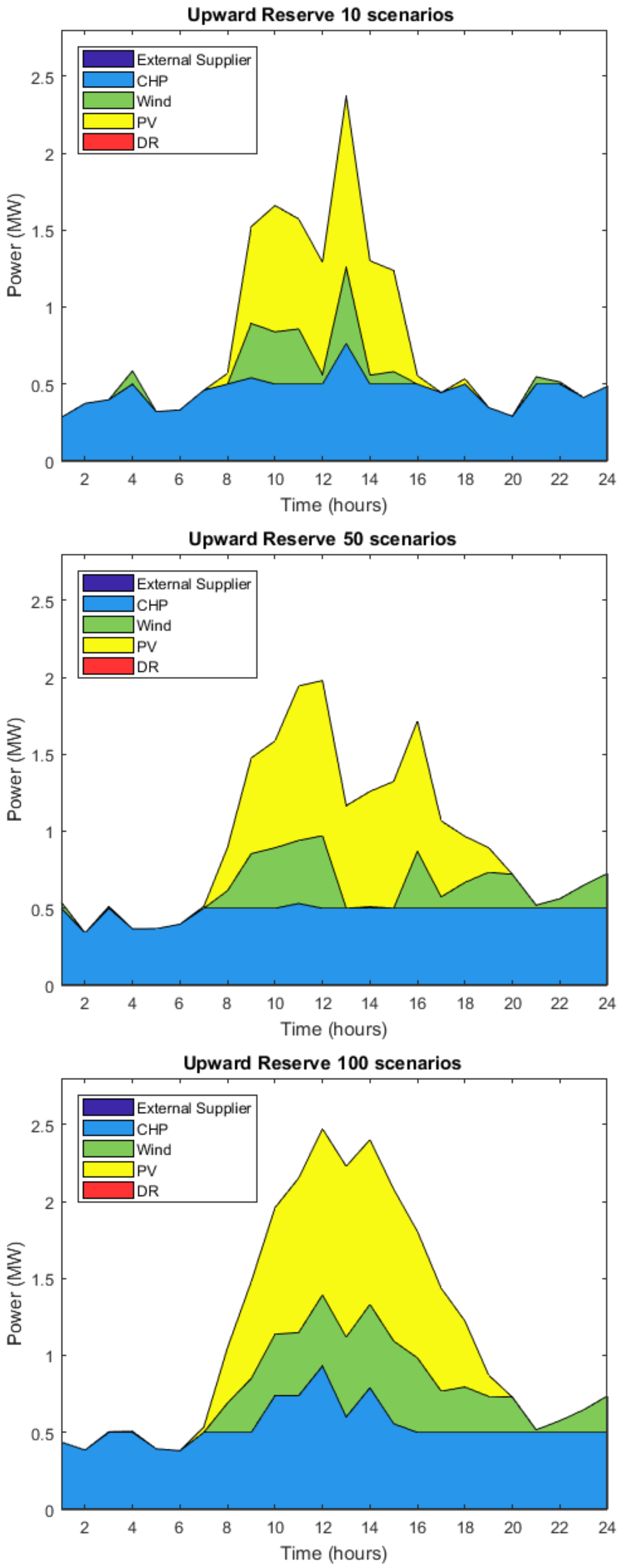

Figure 4.3: Upward reserve scheduled on day-ahead stage by each one of the 28 aggregators along the 24-time periods (considering 10, 50 and 100 scenarios).

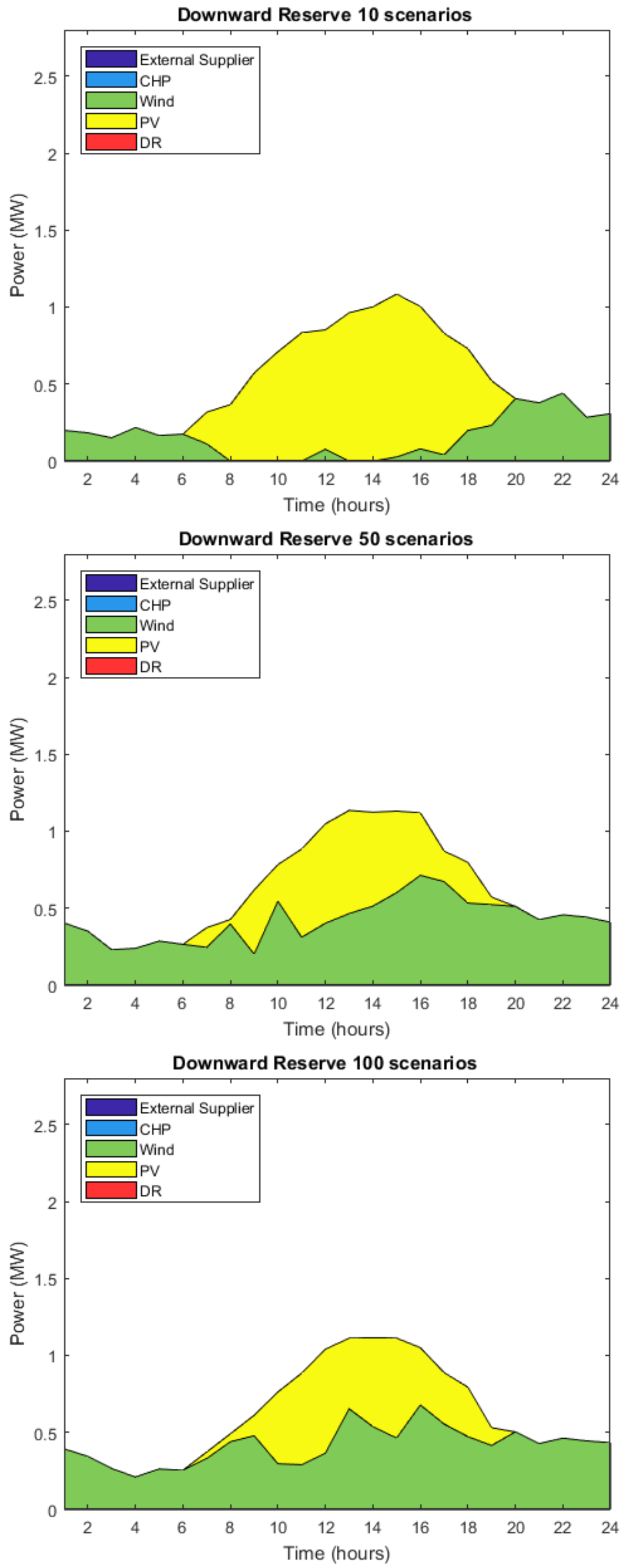

Figure 4.4: Downward reserve scheduled on day-ahead stage by each one of the 28 aggregators along the 24-time periods (considering 10, 50 and 100 scenarios).

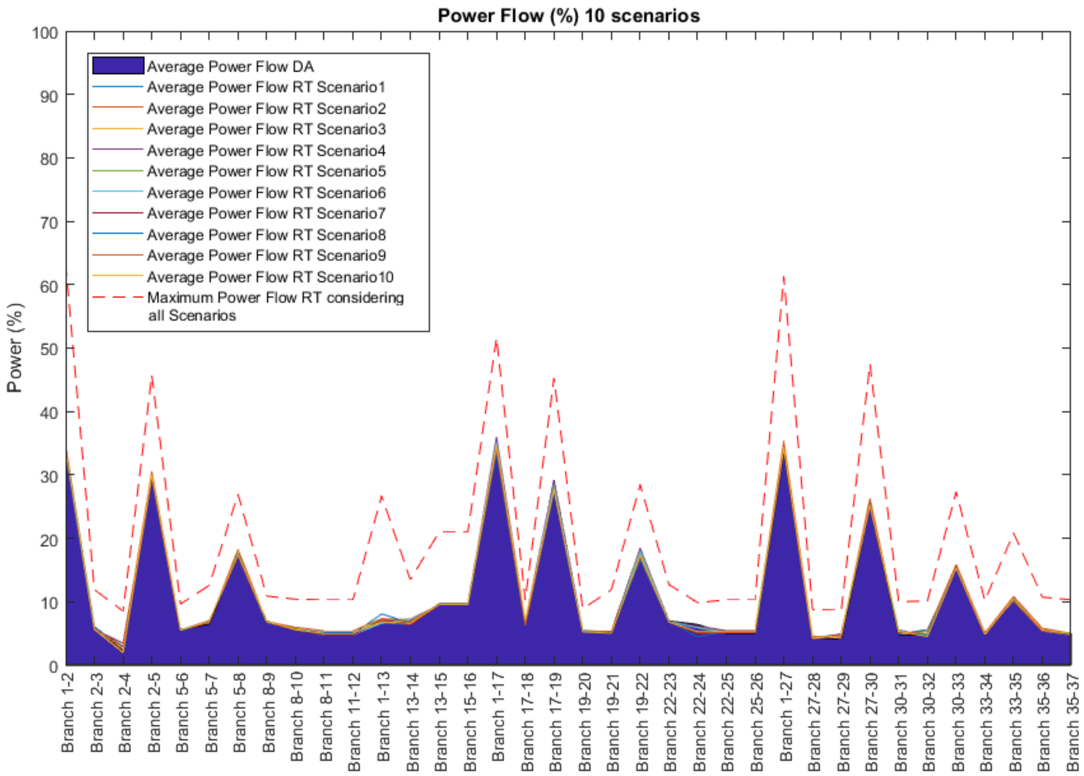

Figure 4.5: Congestion for each one of the 36 lines of the MG (considering 10 scenarios).

4.4.1.1 Quality of the solution - Expected Value of Perfect Information

The Expected Value of Perfect Information (EVPI) represents the quantity that a decision maker is willing to pay for obtaining perfect information about the future. It constitutes a proxy for the value of accurate forecasts [124]. It returns the value of optimal solution when there is no uncertainty and the system operator can make decisions under perfect information. It is calculated removing all the non-anticipative constrains from the original problem. The EVPI index for minimization problems is given in percentage by:

$$EVPI_{MIN}(\%) = \frac{z^{S*} - z^{P*}}{z^{P*}} \times 100 \tag{4.1}$$

where z^{P*} represents the value of the solution when the system operator has perfect information and z^{S*} represents the value of the stochastic solution provided by the simulation of the program.

It is possible to conclude that for periods with high generation by RES, like this case study, the EVPI is larger meaning a greater volatility of the stochastic solution compared to the perfect operating situation (having the perfect information). In fact to have the perfect information, the MG operator is willing to pay 100% more in some time periods.

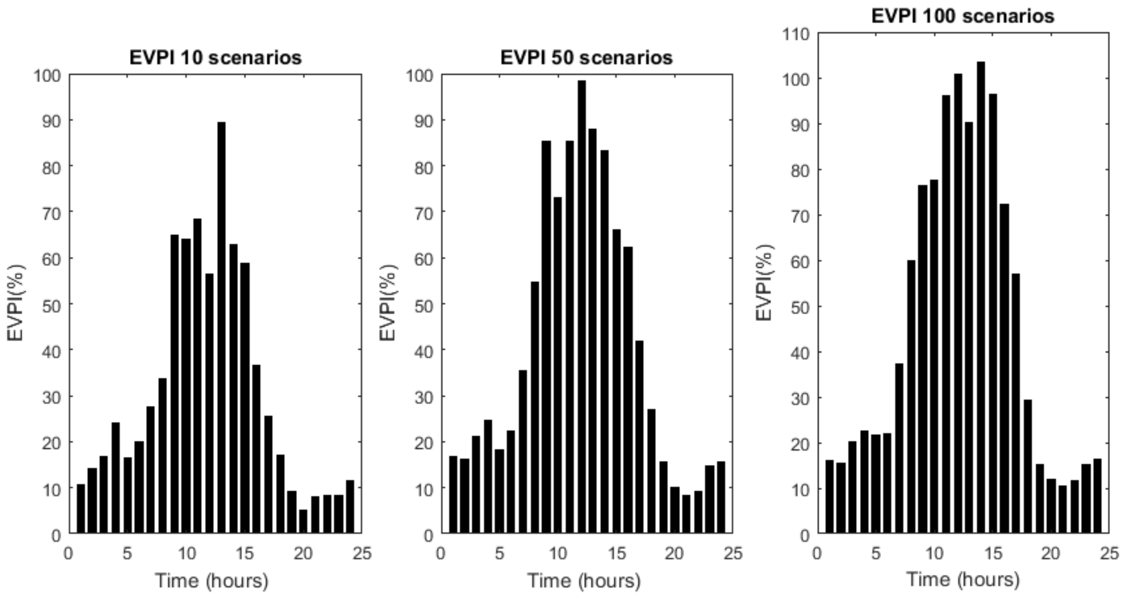

Figure 4.6: EVPI along the 24-time periods (considering 10, 50 and 100 scenarios).

This happens because there is a lot of uncertainty specially during the morning and the afternoon. By overlapping the figures 4.2 and 4.6 is noticeable that the time periods of higher EVPI values correspond to time periods of higher RES generation.

4.4.1.2 Quality of the solution - Value of the Stochastic Solution

The Value of the Stochastic Solution (VSS) is a measure to quantify the advantage of using a stochastic approach instead of a deterministic one, it represents the cost of ignoring uncertainty in choosing a decision. In the deterministic problem associated with stochastic programming, the random variables of the considered stochastic processes are replaced by their respective expected values [124]. The following steps illustrate the calculation process of the index.

1. From the optimal solution results, calculate the arithmetic mean of the second-stage variables;
2. Fix these values on the deterministic model first-stage values;
3. Run the deterministic model. It returns the optimum value for the second-stage variables;
4. Run once again the stochastic model fixing on the first variables, the second-stage deterministic results.

After this steps there was the original stochastic solution with the optimal costs and the solution of the optimal objective function value of the modified stochastic problem (with fixed first-stage decisions), with the associated costs.

The VSS index for the minimization problem is given in percentage by

$$VSS_{MIN}(\%) = \frac{z^{D*} - z^{S*}}{z^{S*}} \times 100 \tag{4.2}$$

where z^{D*} is the solution of the optimal objective function value of the modified stochastic problem (with fixed first-stage decisions).

By the analysis of the figure 4.7 it is concluded that the VSS index has a similar distribution as the EVPI being higher in time periods of more RES generation, meaning that the cost of ignoring the uncertainty is higher on those time periods. This happens due to the same reasons as the EVPI, more uncertainty means a higher expected cost. However when the number of scenarios was enlarged from 10 to 50 to 100, the VSS values decreased some percentage points. The consideration of more scenarios offers a better knowledge of the uncertainty of RES generation, since a better approximation of the probabilistic distribution of production of these resources is obtained. It is easier to see the co-relation between the RES generation and the VSS index when overlapping the figures 4.2 and 4.7.

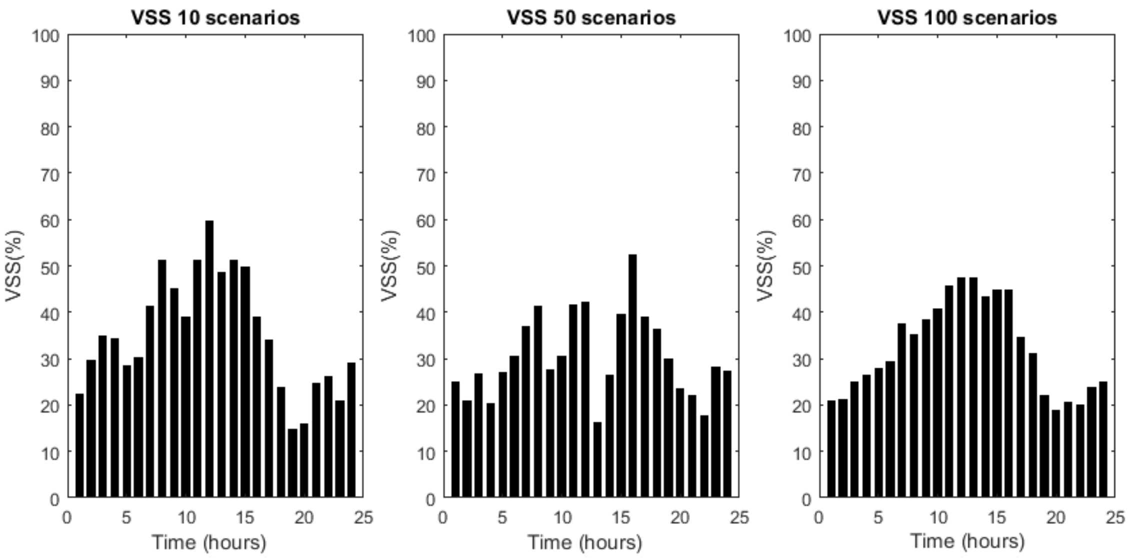

Figure 4.7: VSS along the 24-time periods (considering 10, 50 and 100 scenarios).

4.4.2 Linearized AC model

The results for the AC model are shown here. As in the DC model, the generators are grouped by technology and represented by color in the diagrams. However, as it was explained in 4.3 the results are presented just for 10 scenarios.

During the simulation of the proposed model, it was detected that the linearization of the active and reactive power flow proposed by [61] in the equations 3.16 and 3.17 may not provide accurate results for lines where the resistance (R) is greater the reactance (X) like the grid of this case study.

In fact the author says the power flow linearization is more accurate for transmission lines where R≪X. In order to evaluate the applicability of the linearization method, this model was tested for 3 different situations (R>X, R≈X and R<X) better illustrated on table 4.5. There are two types of cables in the MG and their parameters for x and r are for each case:

Table 4.5: Different values for the resistance of the lines considered for the simulation

	ohm/km			
Cable	X	R (R>X)	R (R≈X)	R (R<X)
LX70	0,119	0,443	0.100	0,0443
LX95	0,113	0,32	0.100	0,032

4.4.2.1 Original case: R>X

The values for R and X have a direct influence on the conductance (G) and susceptance (B) matrixes, respectively. For the original case where R>X the values of the matrix G are large enough to originate, in some lines, power flows with the same signal for the two different directions of the line when solving the equation 3.16. This particularity originates a poor solution with a low level of interest. In fact, when comparing the diagram of the active power in the figure 4.8 with the same diagram of the DC model, it is possible to see that is scheduled less active power, specially in the periods with more consumption.

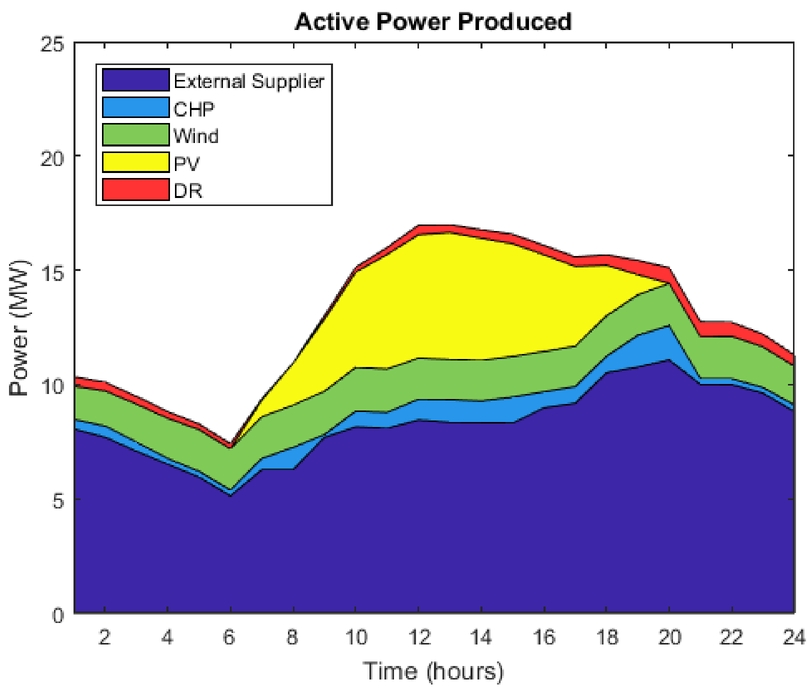

Figure 4.8: Active power delivered on day-ahead stage by each one of the 28 aggregators along the 24-time periods (considering R>X).

Similar problems were encountered solving the power flow equation for the reactive power 3.17. The results for this simulation are presented by the figure 4.9 and it is possible to verify that the MG is practically self-sufficient in terms of reactive power, and from 7h to 20h, it is mostly assured by the PV generators. Only between 2h and 6h and from 22h to 24h the external supplier is providing reactive power. The DR does not provide reactive power.

In the figures 4.10 and 4.11 it is presented the results obtained for upward and downward reserve scheduled in the day-ahead stage, respectively. The values have a significant difference when compared with the DC model. It is scheduled a small amount of upward reserve from the DR resources during the morning. Also, during the night and the first hours of the morning, a great amount of downward reserve is being scheduled, in some cases as much as the active power produced.

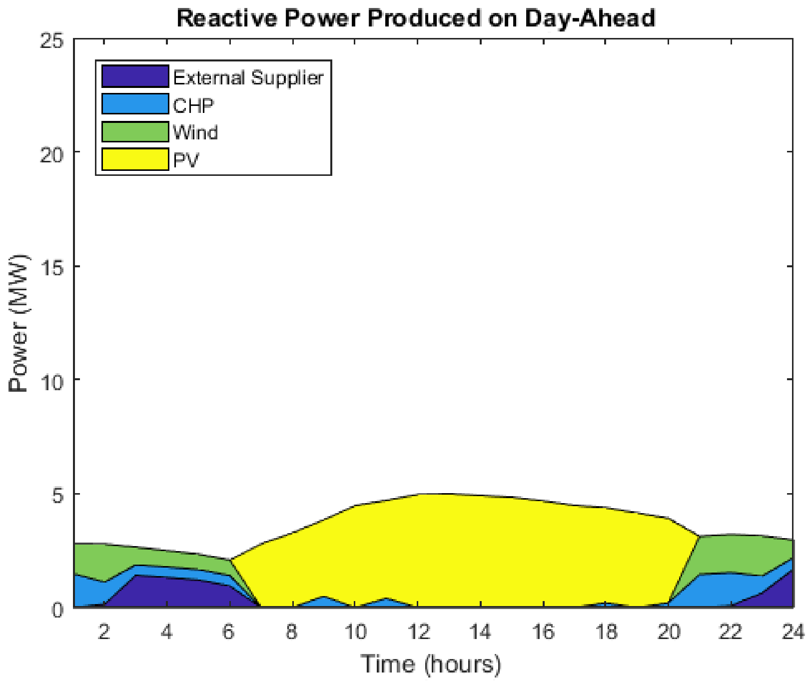

Figure 4.9: Reactive power delivered on day-ahead stage by each one of the 28 aggregators along the 24-time periods (considering R>X).

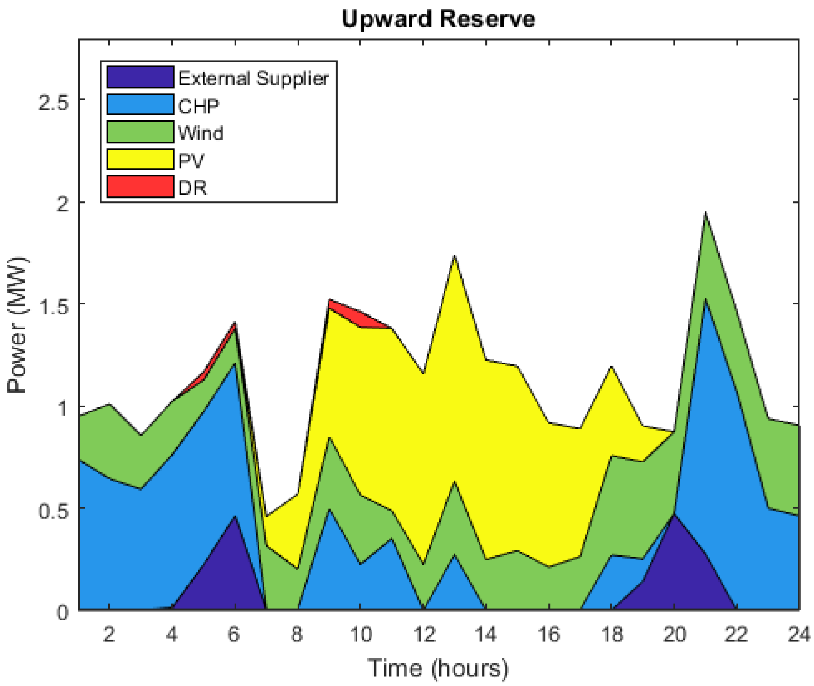

Figure 4.10: Upward reserve scheduled on day-ahead stage by each one of the 28 aggregators along the 24-time periods (considering R>X).

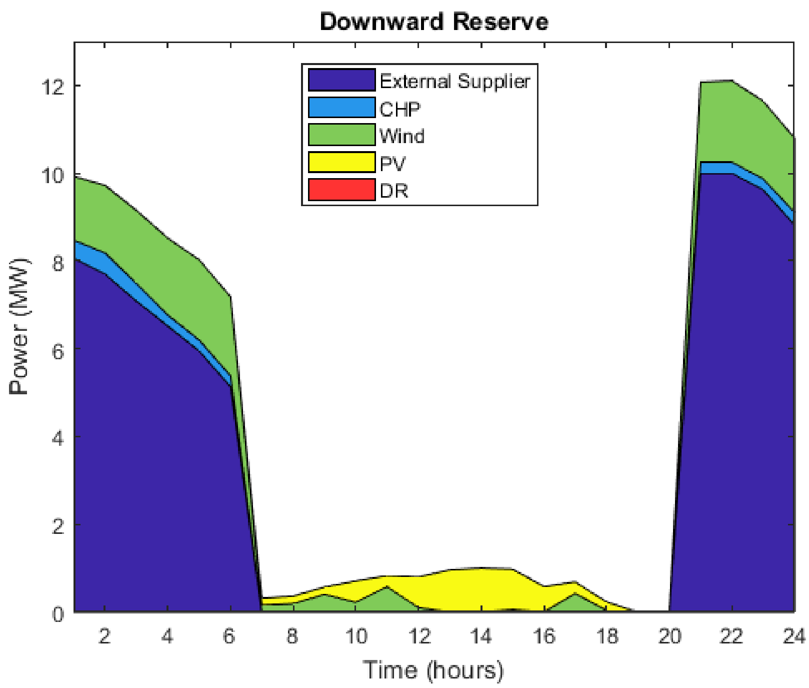

Figure 4.11: Downward reserve scheduled on day-ahead stage by each one of the 28 aggregators along the 24-time periods (considering R>X).

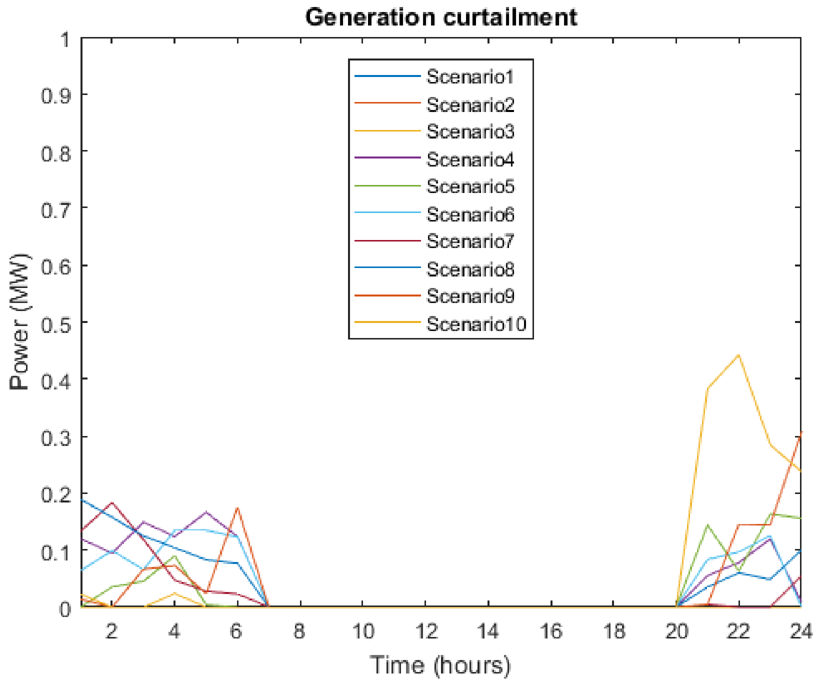

Figure 4.12: Generation curtailment per scenario during the 24-time periods (considering R>X).

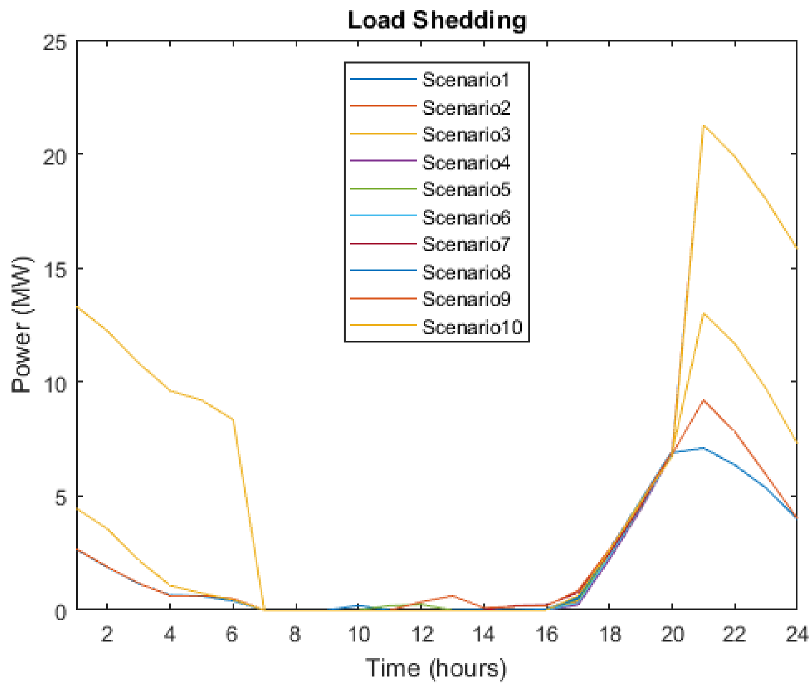

Figure 4.13: Load shedding per scenario during the 24-time periods (considering R>X).

For this conditions (R>X) a small amount of generation curtailment/spillage is activated as it shows the figure 4.12. Also there is a great amount of load shedding in the second-stage as it proves the figure 4.13.

These inconsistencies in the results obtained are direct consequences of linearizing the power flow equations by the approximation 3.16 for a grid where R>X. This exercise was able to prove that this linearization method is not indicated for this type of grids as it is explained by the author in [61]. Next it was tested the same program but with different values for the resistance of the lines.

4.4.2.2 Simulation for R≈X

This subsection contains the results provided by the simulation of the two-stage stochastic programming when the values of the resistance of the lines were changed to R≈X as it is shown in the table 4.5.

For this test there were no inconsistencies in the active and reactive power flow results, proving that the linearization proposed on [61] by the equations 3.16 and 3.17 is accurate for this case.

As it is shown by the figure 4.14, the active power is in conformity with the results of the DC model. The figure 4.15 shows the scheduled reactive power on the day-ahead. It is mainly guaranteed by PV generators when they are available and by the external supplier when they are not. There is also a small amount of DR scheduled during the night and the first hours of the morning.

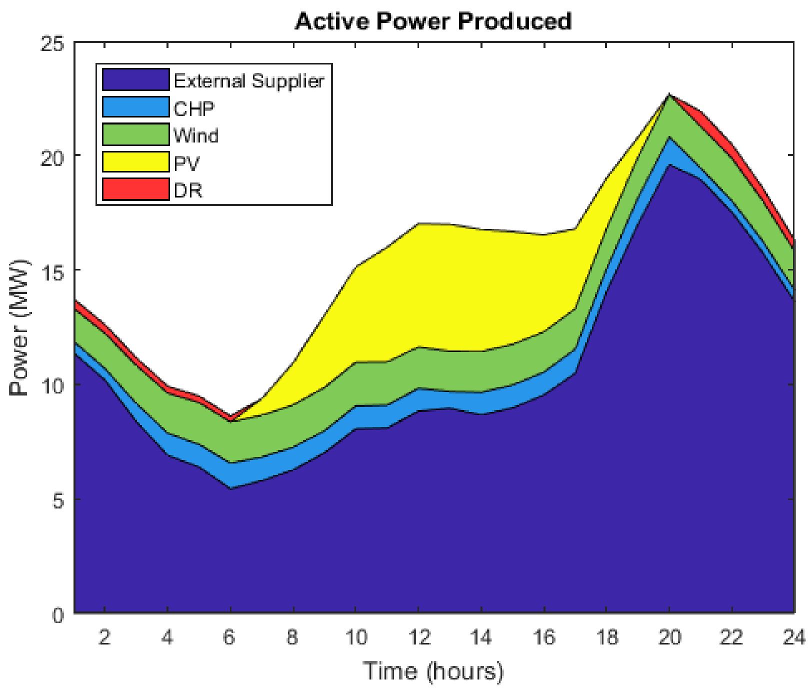

Figure 4.14: Active power delivered on day-ahead stage by each one of the 28 aggregators along the 24-time periods (considering R≈X).

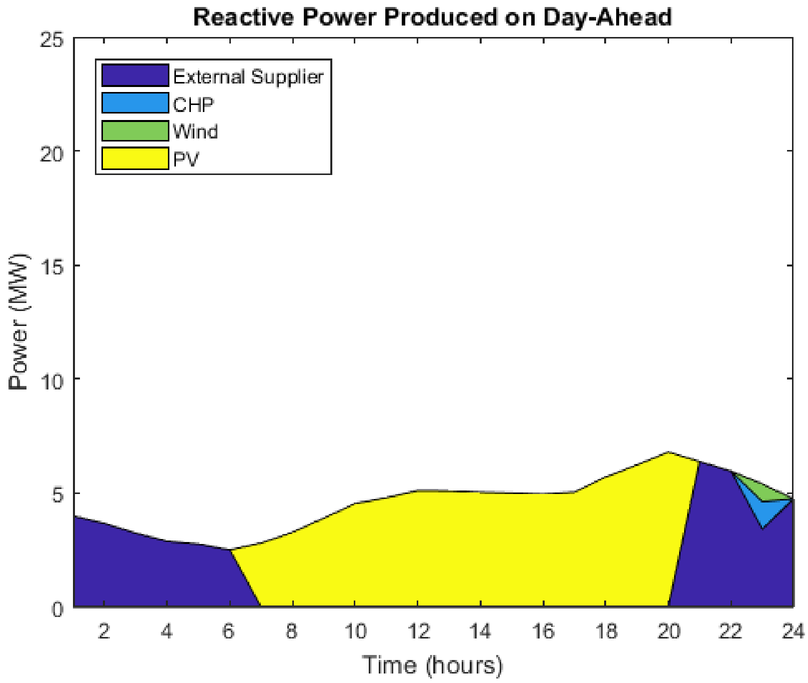

Figure 4.15: Reactive power delivered on day-ahead stage by each one of the 28 aggregators along the 24-time periods (considering R≈X).

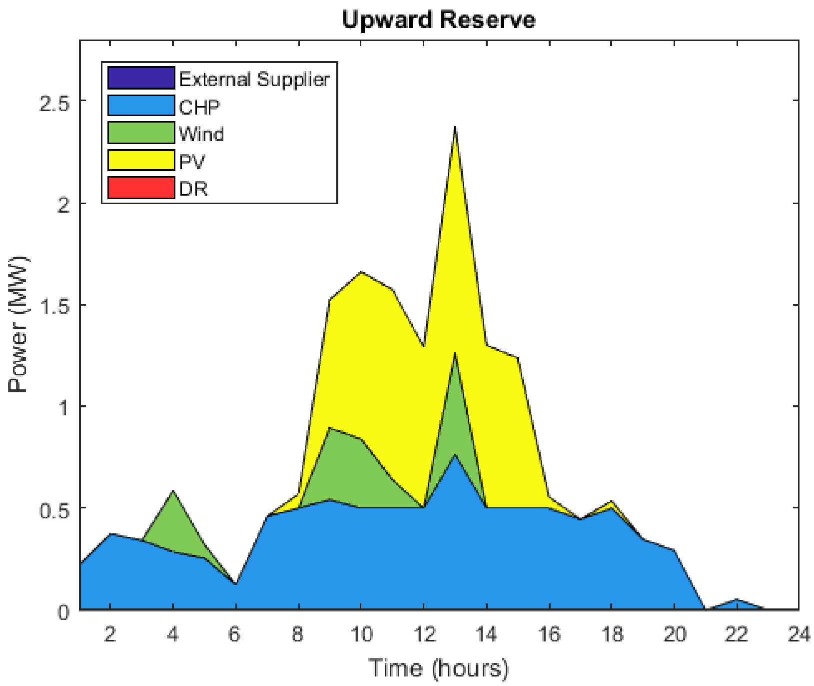

Figure 4.16: Upward reserve scheduled on day-ahead stage by each one of the 28 aggregators along the 24-time periods (considering R≈X).

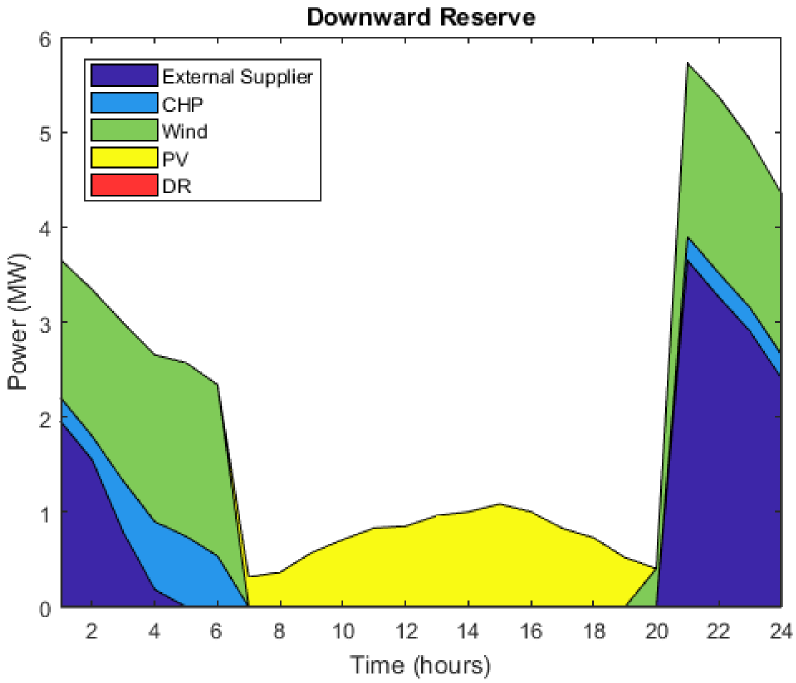

Figure 4.17: Downward reserve scheduled on day-ahead stage by each one of the 28 aggregators along the 24-time periods (considering R≈X).

The figures 4.16 and 4.17 show the upward and downward reserve scheduled on the day-ahead stage, respectively. In this case the amount of upward reserve scheduled is not very different from the DC model, with a small decrease after 21h, however the diagram of the downward reserve has variations when comparing with the DC model. This variation happens because the downward reserve takes part in other constrains in the AC model. Also, a less quantity is scheduled, when compared with the original case (R>X). There is no schedule of upward or downward reserve by the DR resources.

The simulation proved also that there was no need for load shedding in the real-time stage on any scenario, however there were some scenarios with a small amount of curtailment as it can be seen in the figure 4.18.

The figure 4.19 depicts a scheme of the MG. The scheme contains the apparent power flow in percentage of the line capacity and the voltage of the bus. This parameters are represented in terms of colour coded bars on the sides of the image. It is shown the results for the 20h of the scenario 10, which is where the lines have the most congestion (worst case scenario). this was done to prove that the lines are never completely congested in any circumstance.

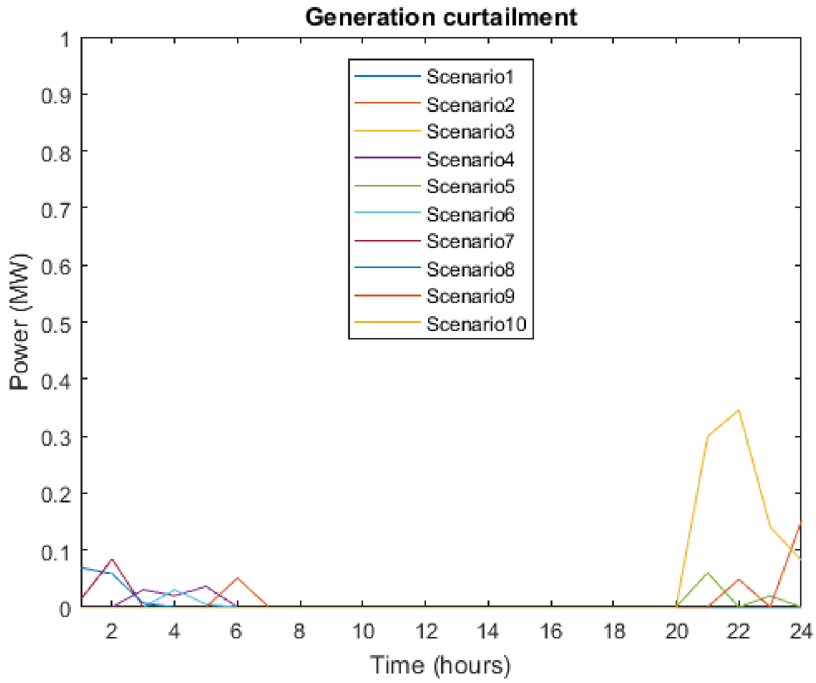

Figure 4.18: Generation curtailment per scenario on real-time stage by each one of the 28 aggregators along the 24-time periods (considering R≈X).

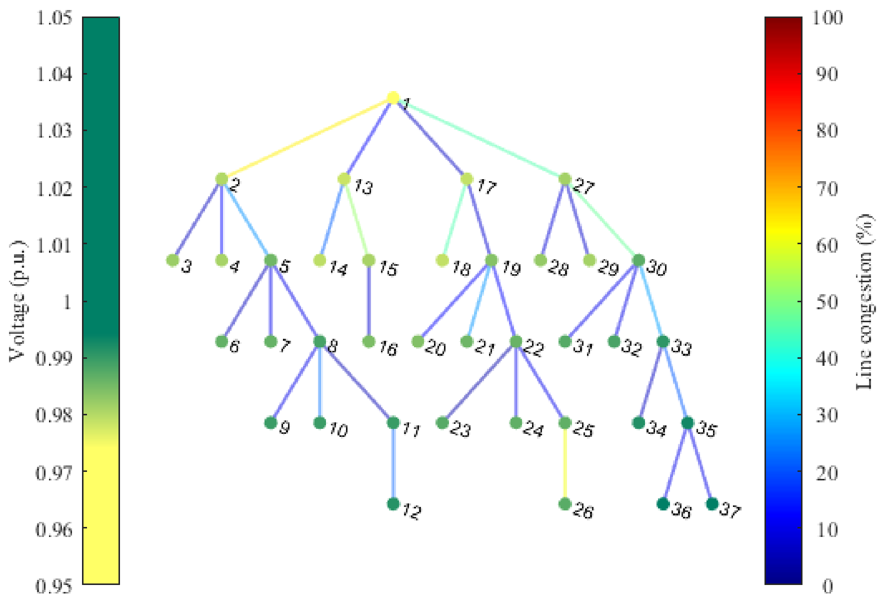

Figure 4.19: Apparent power flow and bus voltage on the worst case scenario and time periods (considering R≈X).

4.4.2.3 Simulation for R<X

In this section are depicted the results of the problem simulation when the values of the resistance of the lines were altered for r<x as it is shown in the table 4.5. These results are expected to be more trustworthy than the case for (R≈X) because the linear approximation of the power flow presented by equations 3.16 and 3.17 are more accurate for grids in which the ratio *X/R* is higher.

In the figure 4.20 is presented the results for the active power scheduled on day-ahead stage and as it was expected, the results are similar with the ones of the DC model and AC for (R≈X). There is also a small amount of DR scheduled during the night and the first hours of the morning.

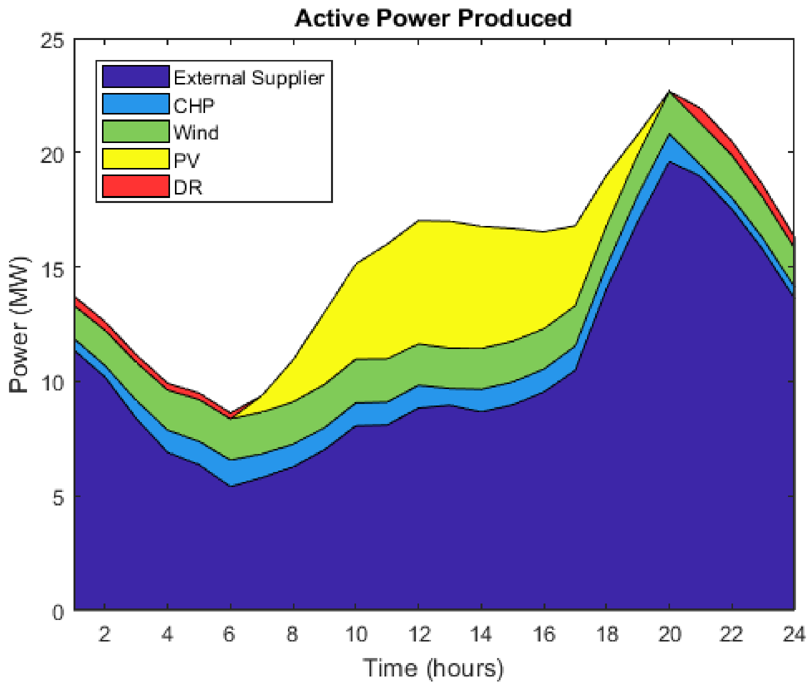

Figure 4.20: Active power delivered on day-ahead stage by each one of the 28 aggregators along the 24-time periods (considering R<X).

The figure 4.21 presents the reactive power scheduled on the day-ahead stage: The diagram is very similar with the one for (R≈X) but the reserve power is solely guaranteed by PV generators and the external supplier.

In the figures 4.22 and 4.23 are presented the upward and downward reserve scheduled on day-ahead stage respectively. The amount of scheduled upward reserve is similar with the case for (R≈X), again with a small decrease after 21h when comparing with the 10 scenarios DC model. The amount of downward reserve scheduled in this case is less than in the case for (R≈X) but the diagram has a similar shape. In both upward and downward reserve schedule, and as in the DC model, the MG is self-sufficient in terms of reserve.

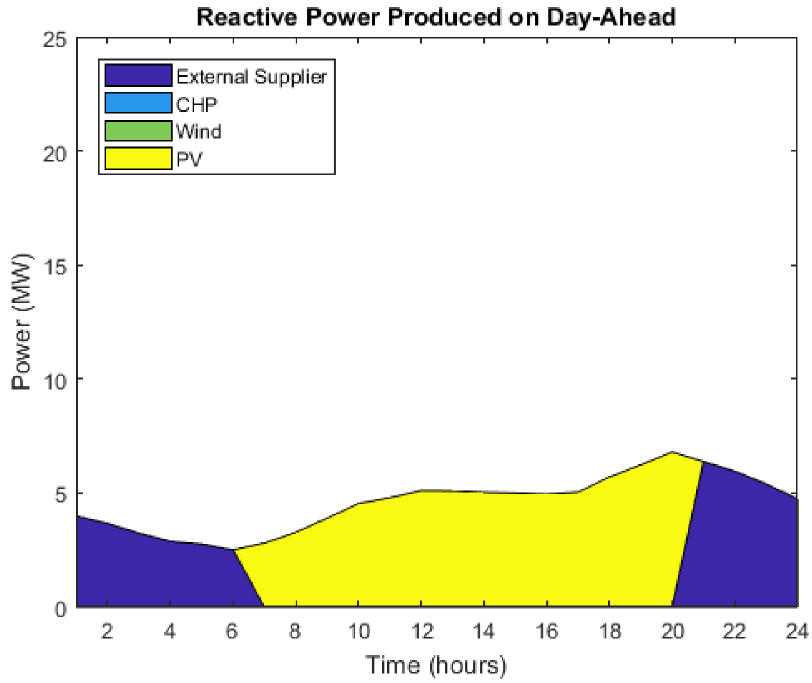

Figure 4.21: Reactive power delivered on day-ahead stage by each one of the 28 aggregators along the 24-time periods (considering R<X).

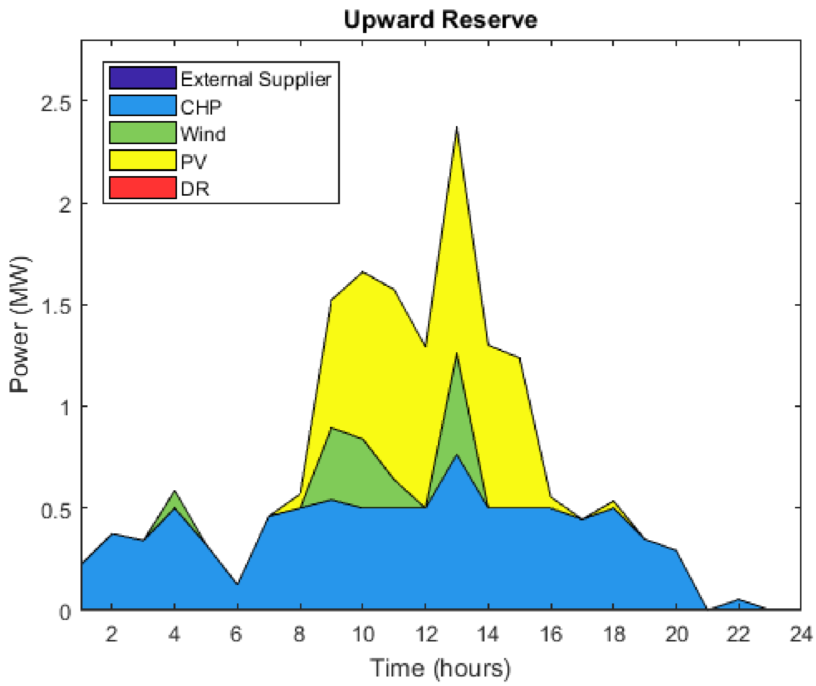

Figure 4.22: Upward reserve scheduled on day-ahead stage by each one of the 28 aggregators along the 24-time periods (considering R<X).

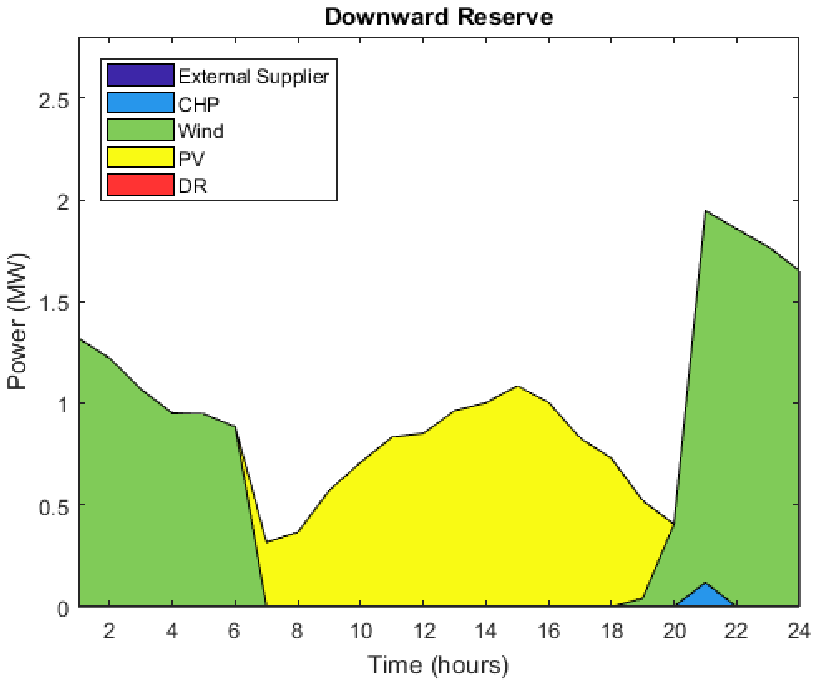

Figure 4.23: Upward reserve scheduled on day-ahead stage by each one of the 28 aggregators along the 24-time periods (considering R<X).

In the figure 4.20 are presented the results for the DR scheduled on day-ahead stage. The results are similar with the ones provides by the simulation of the case for r≈x. By overlapping the figures 4.20 and 4.21 it is noticeable that the DR and the reactive power provided by the external supplier are scheduled in similar proportions for the same time periods during the day-ahead stage.

The optimal solution defined that there was no need for activating the balancing actions of shedding and curtailment.

Finally, the figure 4.24 depicts a MG configuration with the apparent power flow and bus voltage in the same way it was indicated for r≈x by the figure 4.19. In this case it is presented the result for the moment where the load flow on the lines was higher, corresponding to the 21h of the scenario 10. This worst case scenario test proved the lines were never completely congested in any circumstance.

It is noticeable that there are no significant differences in power flow when comparing to the case for R≈X, however it is also noticeable the bus voltages are closer to the lower bound in all the buses.

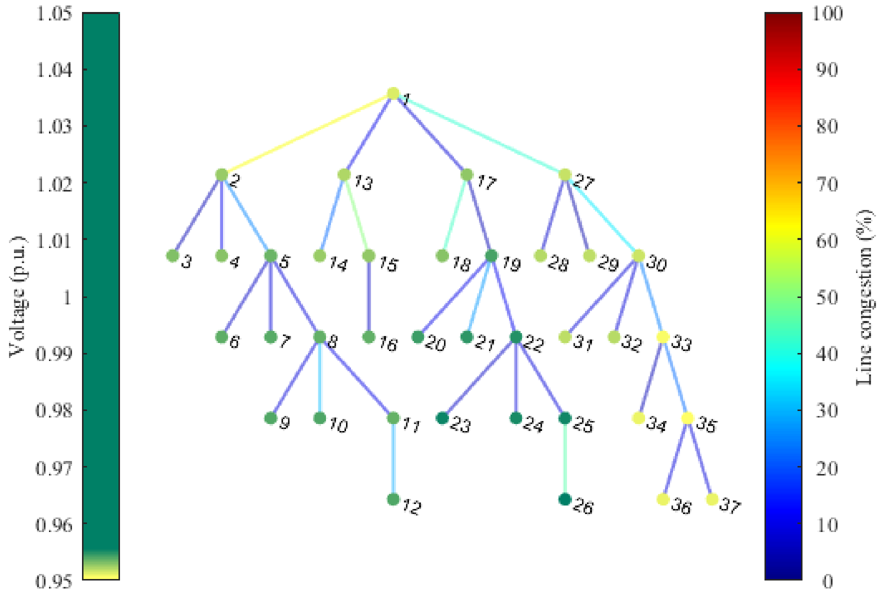

Figure 4.24: Apparent power flow and bus voltage on the worst case scenario and time periods (considering R≈X).

4.4.2.4 Quality of the solution - VSS

The figure 4.25 illustrates the VSS index for the last case tested (R<X). The diagram has a similar shape of the one in DC model, being the VSS higher in periods with more RES generation. For the other cases there were convergence issues and it was difficult to obtain feasible solutions, and for this reason there is only presented the last case tested.

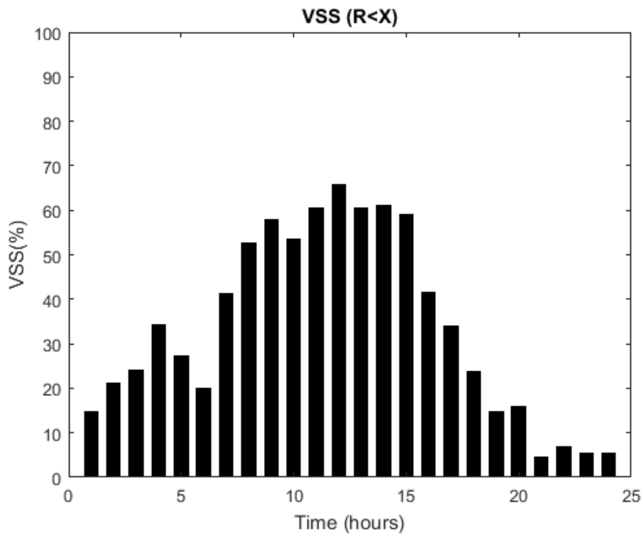

Figure 4.25: VSS along the 24-time periods (considering the 3rd case tested).

4.4.2.5 Quality of the solution - EVPI

By the analysis of the figure 4.26 it is perceived the effect of the *X/R* ratio in the quality of the solution. When this ratio is low as in the initial conditions, the solution is not interesting. When the ratio is high enough, the linearization is accurate and the solution is more reliable.

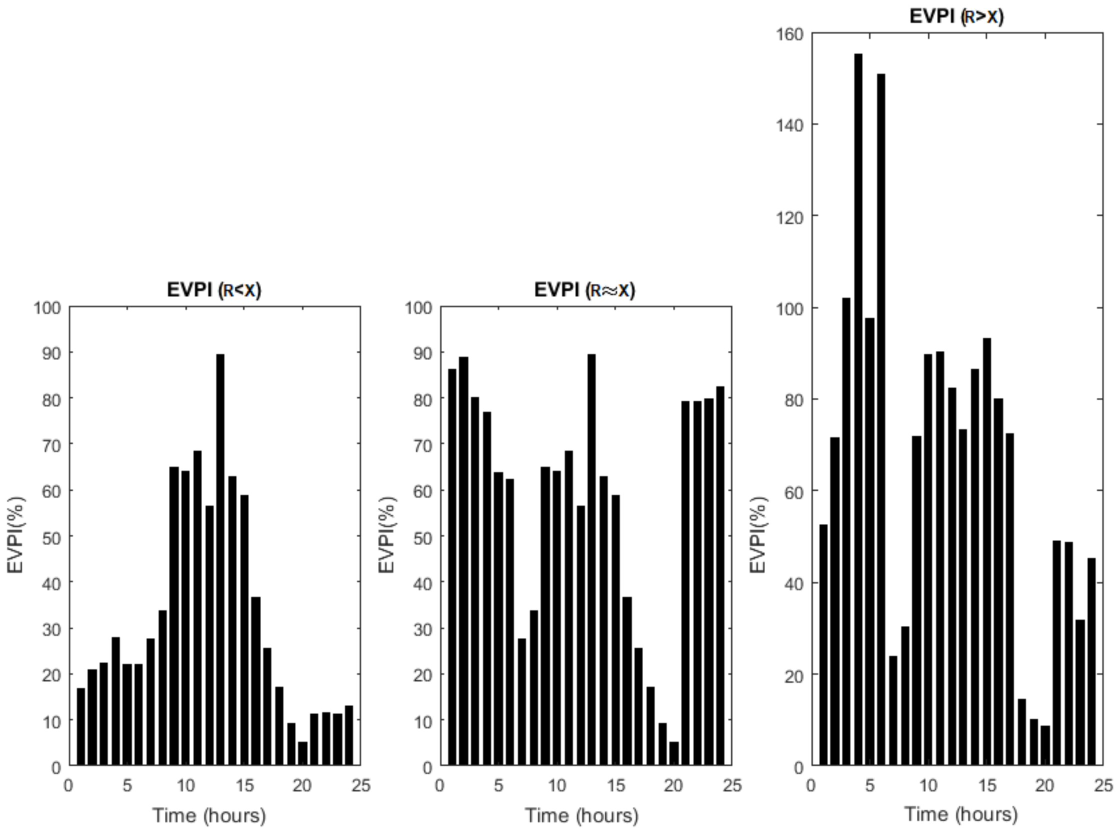

Figure 4.26: EVPI along the 24-time periods (considering the 3 cases tested).

4.4.3 Conclusions of the chapter

The series of tests performed allowed to draw some conclusions about the using of the two-stage stochastic approach for the optimization of energy and reserve in a MG.

The accuracy of the method and the reliability of the solution depends on the level of uncertainty in the system, which directly depends on the level of RES generation. In fact, analyzing the results provided by the quality metrics used (EVPI ans VSS), the program the stochastic solution proved to be further away from the optimal solution (having the perfect information) when there was more RES generation. This means that in periods with high RES generation, the cost of ignoring the uncertainty (translated by VSS value) is significant, and therefore the MG operator is being less efficient. Simultaneously, the cost that the MG operator is willing to pay for obtaining perfect information of RES realization (translated by EVPI value) is also higher.

In addition, there is also a relation between the level of uncertainty and the system costs. In all the tests performed, the cost of the solution was higher in the time periods with more RES generation (more uncertainty). That is, periods with higher RES generation require more reserve to balance the system, thereby increasing the system operating cost.

The AC linear approximation implemented into the stochastic problem used proved to be more accurate for grids with higher ratio *X/R*, demonstrating to not be so effective for distribution lines in which R>X. The first simulation of AC linearized model (R>X) proved to have a low level of interest. The solution was far away from the optimal result, due to a poor linearization of the active and reactive power flows. The third test performed (R<X) was the one in which the linearization is more accurate, and therefore, the one which providing most accurate results. Taking into consideration the second test (R≈X), and contrary to what had been thought before its realization, the solution was not so far from the optimal one. The amount of active energy and reserve scheduled, as well as the active and reactive power flows were similar to the third test and to the DC model. However, there were some differences on the DR scheduling and generation curtailment activation when not fully needed.

The AC linearization method proved to be exceptionally sensitive. Small variations in the cosine piecewise linearization penalty, added in the objective function, were enough to perturb the results, making convergence difficult for an optimal solution. In this scope, several tests were performed using different penalties values and 500 revealed to be an acceptable value which provided reliable results.

Chapter 5

Conclusions and future work

This chapter describes the main conclusions taken from the addressed models on this dissertation. It contains a critical analysis of the proposed methodologies and a discussion of the main results, while highlighting the contributions to the state-of-the-art. Finally, the perspective of future developments in this topic is included.

5.1 Overview of contribution

A MG is a small network of electricity users with a local source of supply that is usually connected to a centralized national grid but is able to function independently. By being a decentralized network configuration, the MG can have numerous benefits for both producers and consumers, comparing with the traditional centralized scheme of the power system. Generation in a MG is provided by small generators with a capacity of the sources ranging from few kW to 1-2 MW, such as wind turbines, PV cells, mini hydro plants, CHP, small diesel generators, etc. [4]. RES such as wind and PV have numerous benefits and their impact on the power system will increase in the future. The proliferation of this type of resources faces many challenges because their power production is uncertain and variable, and therefore uncertainty is costly.

This dissertation focuses on energy and reserve management of a MG under high RES penetration. The aim is to minimize the operating costs of the MG, by obtaining optimal energy and reserve solutions. A two-stage stochastic approach was proposed to address the problem and deal with the uncertain behavior of RES. Uncertainty was modeled in the form of scenarios with an associated probability. The DC OPF was implemented to the aforementioned approach to model the network constraints of a MG, thus avoiding solutions with potential lines congestion. The method shows some advantages. It shows good computational performance and sufficient accuracy to the natural nonlinear behavior of the system. However, for a better approximation of the model to the natural behavior of the MG, different power flow methods can be used, such as AC OPF.

Another important contribution of this dissertation is the inclusion of an recent linearized AC OPF method that allows a better approximation of the natural MG behavior with a slight increase in the computational simulation time. More precisely, the method is able to model active and reactive power and voltage magnitude as opposed to DC OPF. Thus, this approach enables the MG operator to be ready to face potential congestion and voltage problems that may arise in the MG full of DER where bi-directional power flow is common. It should be noted that the AC OPF linearization proposed by [61] and implemented in this dissertation, provides more accurate solutions for grids where the ratio *X/R* is higher. In other cases, the method has some difficulties of convergence (e.g. for networks with R≫X), as explained and proven throughout this dissertation. In fact, the analyses and comparison of different *X/R* ratios are among the contributions of this thesis to the scientific literature under this area of research.

All simulated models were developed using MATLAB software as optimization tool, and solved through the dual-simplex solver. Based on this technique, the most complex model proposed in the development of this work reached 2 hours of simulation. In this way, the proposed model fits the day-ahead market simulation.

5.2 Perspective of future research

Throughout the development of this dissertation, several ideas have arisen to potentially proceed with the evolution of the present work.

Firstly, the reliability of the AC linearization method implemented in this dissertation, for the active and reactive power flow linearization, depends on the impedance value of the lines. For distribution lines like the ones in the MG tested, the ratio *X/R* is normally low and the linearization does not provide an accurate approximation. The future work will focus on an alternative method to do this linear approximation, and which could be applied accurately to distribution networks.

Secondly, a scenario reduction technique can be included. As explained in chapter 4, a large number of scenarios make the problem very demanding in terms of computational resources and with longer run-times. In the case tested, the scenarios had all the same probability and there was no criteria when adding or removing scenarios to perform the tests. For further work, a probabilistic analysis and use of a more efficient scenario reduction technique can be performed.

Lastly, it can be also included a research on the feasibility of integrating ESS on the MG by evaluating the potential cost to be invested and the potential savings for the MG operator.

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